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Weather-integrated machine learning and deep learning framework for long-term solar photovoltaic forecasting in Oman

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Abstract

Accurate long-term solar photovoltaic (PV) power forecasting is essential for renewable energy planning, grid stability, and sustainable energy transition, particularly in regions with high solar potential and climatic variability. This study proposes a weather-integrated hybrid machine learning (ML) and deep learning (DL) framework for long-term solar PV forecasting in Oman using a decade-long daily meteorological dataset (2014–2024) collected from three geographically diverse locations: Izki, Muscat, and Sadah. The framework integrates meteorological variables, including solar radiation, temperature, humidity, rainfall, wind speed, vapor pressure, sunshine duration, and atmospheric pressure. Data preprocessing included missing-value imputation, anomaly correction, normalization, seasonal decomposition, stationarity testing, and cyclical feature engineering to improve forecasting robustness. Conventional statistical approaches (autoregressive integrated moving average, seasonal autoregressive integrated moving average, and exponential smoothing), ML algorithms, and hybrid DL architectures were comparatively evaluated. Results indicate that ensemble regression achieved superior ML performance with validation $R^2 = 0.96$, root mean squared error = 38.60, and mean absolute percentage error = 6.16%, while the recursive long short-term memory + convolutional neural network model with residual correction demonstrated enhanced stability for long-term forecasting horizons. Explainability analysis using Shapley additive explanations and partial dependence plots identified latitude, seasonal encodings, sunshine duration, and atmospheric variables as dominant predictors. The proposed framework provides an interpretable and scalable forecasting solution for renewable energy planning in Oman and similar climatic regions.

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1. Introduction

The accelerating impacts of climate change and the finite nature of fossil fuel resources have underscored the need for a global transition toward clean, sustainable energy systems. Solar energy, as one of the most abundant renewable resources, plays a central

role in this transition. It is highly scalable, environmentally friendly, and increasingly cost-effective (Serban & Lytras, 2020; Sobri *et al.*, 2018). For countries such as Oman, located in the solar-rich Arabian Peninsula, solar energy holds significant potential to reduce dependence on hydrocarbon-based energy sources while addressing energy security (Ghimire *et al.*, 2019; F. Wang *et al.*, 2019). According to the Authority for Public Services Regulation (Huang & Kuo, 2019), Oman receives an average annual solar radiation of over 5.5 kWh/m²/day, ranking it among the highest solar irradiance zones globally. This abundance of solar resources has prompted Oman to increase investments in renewable energy projects, aiming to diversify its energy mix and meet its sustainable development targets, particularly under Oman Vision 2040.

However, while solar energy presents substantial opportunities, its integration into national grids presents significant challenges due to its inherent intermittency. This intermittency arises from variations in meteorological conditions such as cloud cover, humidity, temperature, and wind, leading to fluctuations in solar irradiance and energy production. Accurate solar power forecasting is therefore critical for ensuring grid stability, efficient energy dispatch, and optimal system performance (Shafiullah *et al.*, 2026). While short-term solar forecasting (ranging from minutes to hours ahead) is vital for immediate grid operations, long-term forecasting (spanning months to years) is equally essential for strategic energy planning, infrastructure development, and financial modeling (Kumar *et al.*, 2020). Accurate long-term forecasts allow stakeholders—such as power producers, policymakers, and investors—to make informed decisions about capacity expansion, cost-benefit analyses, and grid reinforcement strategies.

In Oman, long-term solar forecasting has become increasingly important, particularly as the country invests in utility-scale solar projects across diverse locations, such as Ibri, Muscat, and Sadah. Accurate long-term predictions are crucial for assessing the feasibility of such projects, optimizing energy strategies, and ensuring alignment with Oman's renewable energy goals. However, developing reliable long-term solar forecasts remains challenging due to the complexity of meteorological interactions, spatial variability, and the dynamic nature of weather conditions. Traditional forecasting methods often struggle to capture these intricate patterns, particularly over extended periods (Baloch *et al.*, 2024).

To address these challenges, this study proposes an advanced weather-integrated forecasting framework for long-term solar photovoltaic (PV) power prediction in Oman. The framework combines machine learning (ML)

models such as multiple linear regression (MLR), decision tree regressor (DTR), random forest regressor (RFR), gradient boosting regressor (GBR), extreme GBR (XGBR), and ensemble regression (ER) with deep learning (DL) architectures, including long short-term memory (LSTM) networks, convolutional neural networks (CNN), and hybrid LSTM + CNN models. These models are designed to capture both linear and nonlinear relationships in meteorological data, enabling more accurate and robust long-term predictions (Jung *et al.*, 2020; D. Yang *et al.*, 2018).

The novelty of this research lies in its comprehensive integration of weather data, the development of a hybrid modeling framework that fuses classical ML with DL, and the introduction of a new definition of long-term prediction, which is based on the proportion of training to testing data (i.e., forecasting over 50% of the training data duration). This framework is expected to enhance the reliability of solar energy forecasts, ultimately improving PV system performance and enabling the effective implementation of renewable energy strategies in Oman. Moreover, the study offers valuable insights into the potential for hybrid and ensemble models to overcome the limitations of traditional methods in complex, dynamic forecasting environments. The remainder of this paper is organized as follows: **Section 2** presents the literature review. **Section 3** describes the dataset and methodology. **Sections 4** and **5** discuss the results and model evaluation. **Section 6** concludes the study and presents future research directions.

2. Literature review

Solar energy forecasting is a critical task for integrating solar power into the grid, optimizing PV system performance, and supporting energy policy formulation (Carlak & Karabanova, 2026). Accurate solar forecasting allows energy producers, operators, and policymakers to anticipate production levels, manage grid stability, and avoid over-reliance on non-renewable energy sources (Shamshirband *et al.*, 2019). The process of solar energy forecasting is inherently complex due to the dynamic and stochastic nature of meteorological variables such as solar radiation, temperature, humidity, wind speed, and atmospheric pressure. These factors exhibit intricate nonlinear interactions that require advanced forecasting techniques capable of capturing their complex relationships over short-term and long-term horizons (Azizi *et al.*, 2023).

In recent years, ML and DL techniques have emerged as powerful tools for improving solar energy forecasting accuracy (Raza *et al.*, 2026). Classical statistical models, such as MLR and autoregressive integrated moving

average, were widely used for solar forecasting in earlier studies. These models, while simple and interpretable, often fail to capture the complex, nonlinear relationships in meteorological data, limiting their predictive accuracy (Alotaibi *et al.*, 2020). As a result, there has been a significant shift towards ML techniques, which are better suited for handling the high-dimensional, multivariate nature of meteorological data (Antonanzas *et al.*, 2016).

Among ML techniques, random forests, gradient boosting (GB), and extreme GB (XGBoost) have demonstrated strong predictive performance in solar energy forecasting. Random forest is an ensemble learning method that aggregates multiple decision trees, offering improved accuracy, robustness, and generalizability by reducing overfitting (Yap *et al.*, 2020). Similarly, GB and XGBoost build trees sequentially to correct errors made by previous models, which enhances their ability to handle noisy and high-dimensional data (Nishant *et al.*, 2020; Notton *et al.*, 2018). These techniques have been successfully applied in solar radiation forecasting across various climates, including regions with high solar irradiance (Koprinska *et al.*, 2018; F. Wang *et al.*, 2020). Furthermore, ensemble methods, such as ER, which combine predictions from base models, have shown promise in improving predictive accuracy and reducing model bias and variance (Mellit & Kalogirou, 2008).

On the other hand, DL methods, particularly LSTM networks, have gained significant attention for time-series forecasting due to their ability to model sequential data and capture long-term temporal dependencies (Haroun *et al.*, 2025; Yaghoubi *et al.*, 2025). LSTMs are a type of recurrent neural network (RNN) designed to handle vanishing gradient problems and maintain memory over long sequences, making them highly effective for forecasting applications where past observations influence future outcomes (Hossain *et al.*, 2019). LSTM models have demonstrated considerable success in forecasting solar radiation over time horizons ranging from hours to days, as they can learn both long-term and short-term temporal dependencies (H. Wang *et al.*, 2020).

In addition to LSTMs, CNNs have been applied in solar radiation forecasting to capture local temporal patterns and spatial correlations. CNNs are particularly useful for detecting fine-grained structures in the input data, which enhances the model's ability to predict short-term fluctuations in solar radiation (Vanegas Cantarero, 2020). CNNs have been incorporated into hybrid models, such as LSTM + CNN, to combine the strengths of both architectures. These hybrid models are able to simultaneously learn from temporal dependencies (through LSTM) and spatial patterns (through CNN), thus

providing a more robust approach for complex forecasting tasks (Lee *et al.*, 2019). Hybrid LSTM + CNN models have been shown to outperform standalone models in capturing the complex dynamics of solar radiation, particularly in multi-step forecasting (P. Li *et al.*, 2020; Sheng *et al.*, 2018).

Despite the advancements in ML and DL for solar energy forecasting, challenges remain in defining and applying long-term prediction strategies. While short-term forecasts (minutes to hours ahead) are well-established and have been widely adopted in operational settings (Rajagukguk *et al.*, 2020), long-term forecasting (spanning months to years) is less explored and presents unique difficulties due to the seasonal and interannual variability of meteorological conditions (Baloch *et al.*, 2025). For instance, long-term forecasting requires models to account for changes in climate patterns, such as shifts in temperature, humidity, and precipitation, which influence solar radiation over extended periods. To address this, recent studies have begun exploring the integration of seasonal and exogenous variables, such as humidity and wind speed, in improving long-term solar forecasts (Le *et al.*, 2019; Y. Li *et al.*, 2014).

Existing studies have often used long-term solar forecasting over a single site or limited geographic regions. However, few studies have comprehensively compared the performance of different models across multiple regions with diverse climatic conditions, as is the case in Oman (Haroun *et al.*, 2025; Yaghoubi *et al.*, 2025). This gap in the literature underscores the need for robust, general-purpose forecasting frameworks adaptable across different geographic locations. Furthermore, there is a lack of clear definitions and consistent benchmarks for what constitutes “long-term” solar forecasting in the context of ML and DL models. Although several studies have defined long-term forecasting based on the duration of the prediction relative to the available dataset (e.g., more than 50% of the training data), a unified approach remains lacking (K. Li *et al.*, 2019; Srivastava & Lessmann, 2018).

The current study seeks to fill these gaps by proposing a comprehensive framework for long-term solar PV power prediction in Oman. By integrating a decade-long dataset of meteorological parameters, this study develops a hybrid ML and DL-based forecasting model that captures both short- and long-term variations in solar radiation. Additionally, this study introduces a new definition of long-term prediction based on the proportion of training and testing data, enabling a clearer understanding of the forecasting horizon and its associated challenges. The insights from this study contribute to improving solar PV forecasting and to enhancing the adoption of renewable energy strategies in Oman and other regions with similar climatic conditions (Behera *et al.*, 2018).

3. Research methodology

This section presents the overall methodological framework adopted for developing and evaluating the proposed long-term solar PV forecasting system. It describes the dataset characteristics, preprocessing procedures, feature engineering techniques, forecasting models, evaluation metrics, and validation procedures used to ensure robust and reliable model development.

3.1. Dataset description

This subsection describes the characteristics of the dataset used for forecasting solar radiation and PV power generation in Oman. It includes information regarding data sources, study locations, meteorological variables, temporal coverage, and preprocessing strategies adopted to improve data quality and model reliability.

3.1.1. Data sources and collection

This study utilized a comprehensive dataset compiled from three principal institutions: the Directorate General of Meteorology, the Muscat Energy Company, and the Oman Solar Systems Company, spanning the period from 2014 to 2024. These organizations provided validated environmental and meteorological measurements across three geographically diverse sites in Oman: Izki, Muscat, and Sadah. The selection of these locations allowed for broad representativeness in modeling solar energy forecasting across varying terrain and climatic zones (Golestaneh *et al.*, 2016).

The collected data included daily observations of solar radiation and auxiliary weather parameters. Quality control measures included interpolation for missing values and correction of anomalies, particularly for global radiation (GR) values below 200 mWh/cm², which were removed or corrected in alignment with prior practices in solar forecasting studies (A. Ahmed & Khalid, 2019; Kushwaha & Pindoriya, 2019).

3.1.2. Description of variables

The dataset used in this study included a diverse set of variables critical to accurately forecasting the dependent variable, solar radiation. These parameters were selected based on their demonstrated physical and statistical relevance in solar PV forecasting literature (Alizadeh *et al.*, 2020; Zang *et al.*, 2020). As detailed in Table 1, the variables included GR, various geographical descriptors (latitude, longitude, elevation), and meteorological conditions (air temperature [AT], relative humidity [RH], vapor pressure, wind speed and direction, sunshine duration [SD], station-level pressure, and rainfall). Each of these was captured through multiple temporal dimensions (mean, maximum,

and minimum), enhancing the dataset's granularity and its capacity to model short- and long-term variability. This multidimensional structure was particularly advantageous in ML and hybrid DL models, which benefit from rich temporal features when forecasting solar output (Theo *et al.*, 2017; X.-S. Yang, 2021). The inclusion of atmospheric parameters like vapor pressure and pressure levels further strengthened the dataset's applicability to dynamic climate modeling, as these factors influence cloud formation and solar transmissivity (Bajaj & Singh, 2020). By organizing variables into dependent and independent categories with clear units and abbreviations, the dataset aligned well with contemporary solar forecasting practices and facilitated robust model training and evaluation.

3.1.3. Geographic and temporal scope

The dataset spanned 2014–2024 and covered three Omani sites: Izki, Muscat, and Sadah, each representing distinct climatic conditions. This geographic diversity strengthens model generalizability by incorporating varied solar and weather patterns (Ahmad *et al.*, 2018). Key parameters included solar radiation, temperature, humidity, wind speed, rainfall, and pressure. As shown in Table 2, Muscat recorded the highest mean solar radiation, while Sadah exhibited greater humidity and wind variability. All sites had low missing data (< 0.1%) and over 3,400 records, ensuring the robustness of the dataset for ML applications in long-term solar energy forecasting.

3.1.4. Data visualization

To better understand the characteristics of the dataset, three types of visualizations were used: box plots, a correlation heatmap, and distribution plots. As shown in Figure 1, box plots revealed the variability and spread of key meteorological parameters across Izki, Muscat, and Sadah. Muscat exhibited the highest median solar radiation and SD, while Sadah showed greater variability in wind speed and rainfall. Izki demonstrated stable, moderate conditions across most parameters, making it suitable for baseline comparisons. Figure 2 presents a correlation heatmap, illustrating the interrelationships among variables. Strong positive correlations were observed between solar radiation and SD ($r > 0.8$), whereas negative correlations were observed between solar radiation and humidity. These trends are consistent with previous findings in solar forecasting (Madeti & Singh, 2017a; Şen, 2008). Figure 3 displays parameter distributions across all sites. Most variables followed near-normal distributions, with exceptions like wind speed, which were positively skewed due to sporadic extreme values. Understanding these distributions is vital for selecting appropriate preprocessing techniques and modeling methods (Seyedmahmoudian *et*

Table 1. Dataset variables and characteristics (units, types, abbreviations)

Parameter		Unit	Abbreviation	Variable type
Global radiation		mWh/cm ²	GR	Dependent
Latitude		Decimal degree	–	Independent
Longitude		Decimal degree	–	Independent
Elevation		Meter (m)	–	Independent
Wind direction		°	WSD	Independent
Sunshine duration		Hours (h)	SD	Independent
Station-level pressure (SLP)	Mean	hPa	SLP_Mean	Independent
	Maximum	hPa	SLP_Max	Independent
	Minimum	hPa	SLP_Min	Independent
Air temperature (AT)	Mean	°C	AT_Mean	Independent
	Maximum	°C	AT_Max	Independent
	Minimum	°C	AT_Min	Independent
Vapor pressure (VP)	Mean	hPa	VP_Mean	Independent
	Maximum	hPa	VP_Max	Independent
	Minimum	hPa	VP_Min	Independent
Relative humidity (RH)	Mean	%	RH_Mean	Independent
	Maximum	%	RH_Max	Independent
	Minimum	%	RH_Min	Independent
Wind speed (WS)	Mean	Knots	WS_Mean	Independent
	Maximum	Knots	WS_Sust	Independent
	Minimum	Knots	WS_Gust	Independent
Rainfall (RF)	Total	Mm	RF_Total	Independent
	10 min	Mm	RF_Max_10min	Independent
	1 h	Mm	RF_Max_1h	Independent

Table 2. Summary statistics of datasets per site (Izki, Muscat, Sadah)

Parameter	Unit	Izki (mean ± standard deviation)	Muscat (mean ± standard deviation)	Sadah (mean ± standard deviation)
Solar radiation	mWh/cm ²	465.72 ± 128.45	487.39 ± 135.87	421.28 ± 142.90
Temperature	°C	27.65 ± 6.22	29.80 ± 5.47	26.34 ± 6.88
Relative humidity	%	47.20 ± 15.10	51.78 ± 17.33	57.64 ± 18.59
Wind speed	m/s	2.15 ± 1.02	1.90 ± 0.98	3.02 ± 1.35
Atmospheric pressure	hPa	1,008.7 ± 4.35	1,012.5 ± 3.98	1,002.9 ± 5.21
Sunshine duration	Hours/day	9.12 ± 2.88	10.35 ± 2.43	8.90 ± 3.15
Rainfall	Mm	2.38 ± 4.91	3.20 ± 6.17	4.85 ± 8.22
Vapor pressure	hPa	14.85 ± 3.44	17.22 ± 4.01	13.78 ± 2.89
Number of records	Count	3,606	3,495	3,408
Missing values (%)	%	0.03%	0.05%	0.08%

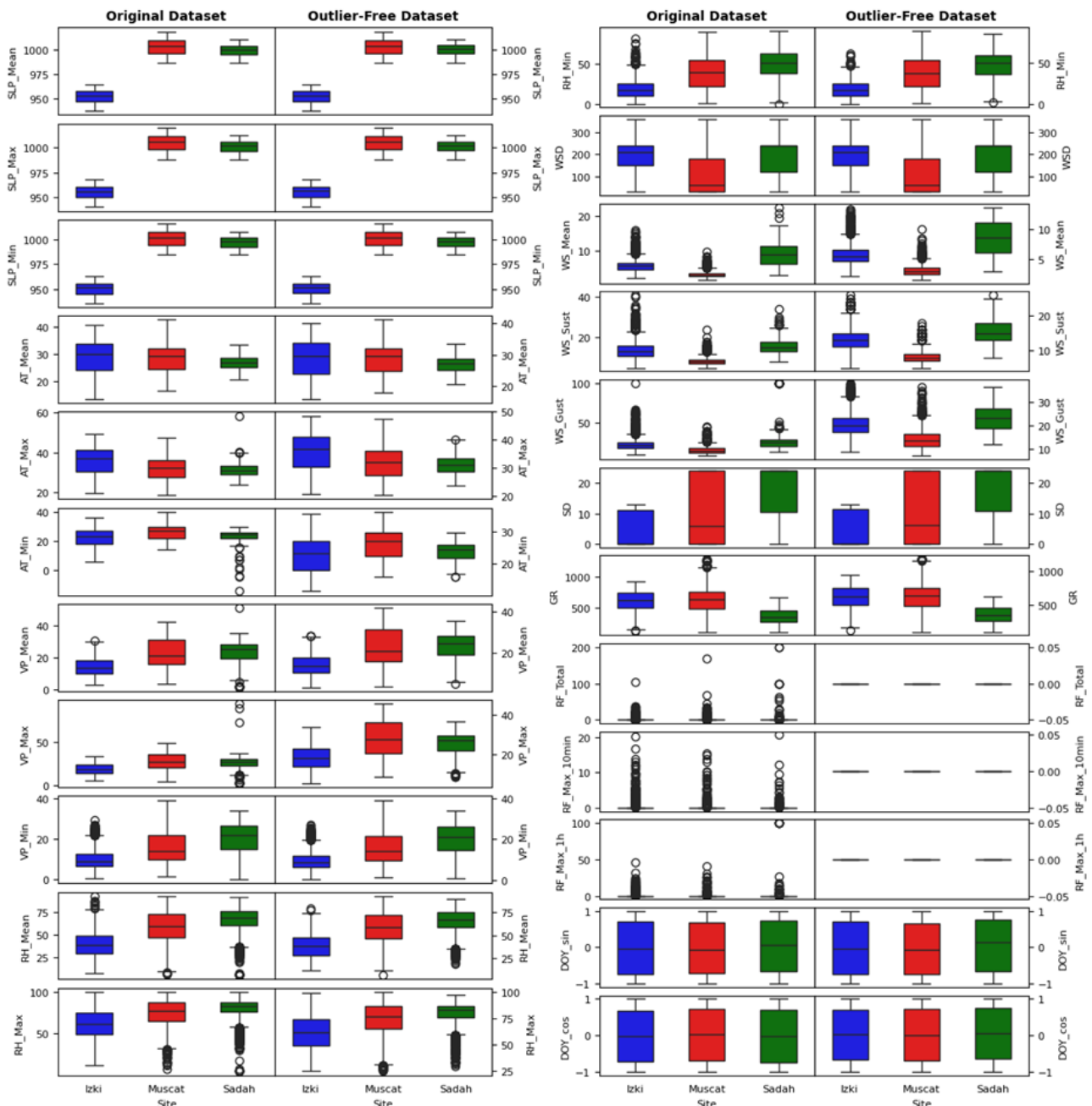


Figure 1. Box plot of meteorological parameters

Abbreviations: AT: Air temperature; DOY: Day of the year; GR: Global radiation; RF: Rainfall; RH: Relative humidity; SD: Sunshine duration; SLP: Station-level pressure; VP: Vapor pressure; WS: Wind speed; WSD: Wind direction.

al., 2016; Zhou *et al.*, 2020). Together, these visualizations guide model development by highlighting data behavior, trends, and potential anomalies. Figure 4 illustrates the preprocessing and decomposition of GR data across three Omani sites—Izki, Muscat, and Sadah—using methods

aligned with prior solar forecasting studies (Kabir *et al.*, 2018; Nižetić *et al.*, 2019). The top panels demonstrate the transformation from raw datasets to interpolated and cleaned versions, significantly improving continuity and reducing noise, especially in Sadah, which initially exhibited

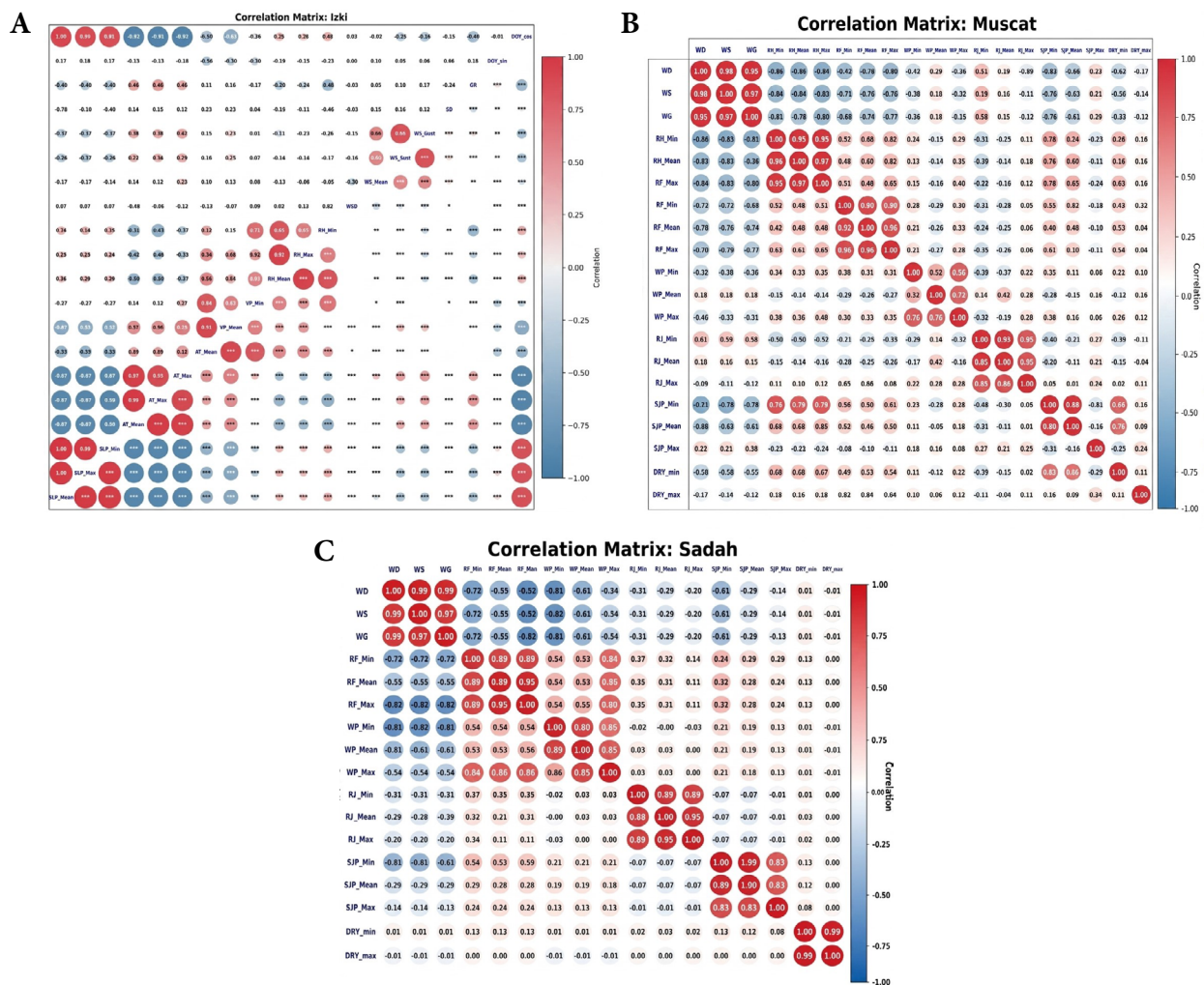


Figure 2. Correlation heatmap (full dataset). (A) Correlation matrix: Izki. (B) Correlation matrix: Muscat. (C) Correlation matrix: Sadah. Abbreviations: AT: Air temperature; DOY: Day of the year; GR: Global radiation; RH: Relative humidity; SD: Sunshine duration; SLP: Station-level pressure; VP: Vapor pressure; WS: Wind speed; WSD: Wind direction.

severe anomalies. The bottom panels apply classical time series decomposition to separate GR into trend, seasonal, and residual components. This reveals consistent annual seasonality across all sites, a steady upward trend from 2016 to 2021, and lower residual variance in Izki compared to Muscat and Sadah, supporting the importance of robust preprocessing for accurate long-term forecasting (Ma *et al.*, 2018; Mellit *et al.*, 2020).

3.2. Data preprocessing for time-series forecasting

Effective time-series forecasting requires rigorous data preprocessing to ensure statistical integrity and modeling readiness. In this study, preprocessing was performed across multiple stages—ranging from raw data cleaning

to transformation and stationarity testing—on daily solar radiation datasets from the three Omani sites: Izki, Muscat, and Sadah.

3.2.1. Original dataset and cleaning procedures

The initial dataset included daily records of GR and associated meteorological parameters collected from 2014 to 2024. These data were obtained from the Directorate General of Meteorology, Muscat Energy Company, and Oman Solar Systems Company. Upon inspection, several anomalies were observed—particularly GR values below 200 mWh/cm², which were either physically implausible or caused by sensor faults or cloud-induced shading. Following the methodologies outlined by Assouline *et al.*

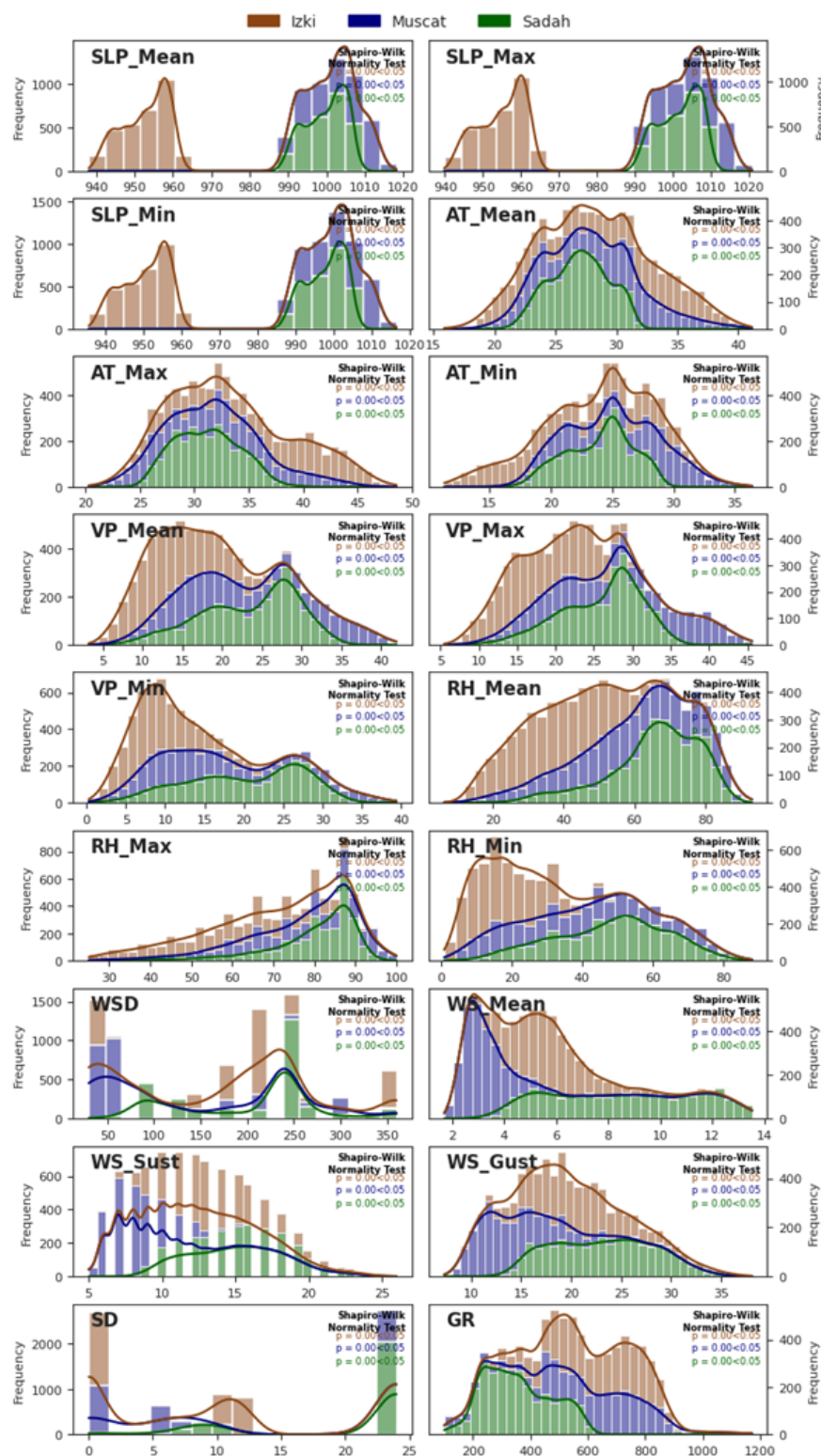


Figure 3. Dataset distribution (full dataset)

Abbreviations: AT: Air temperature; DOY: Day of the year; GR: Global radiation; RH: Relative humidity; SD: Sunshine duration; SLP: Station-level pressure; VP: Vapor pressure; WS: Wind speed; WSD: Wind direction.

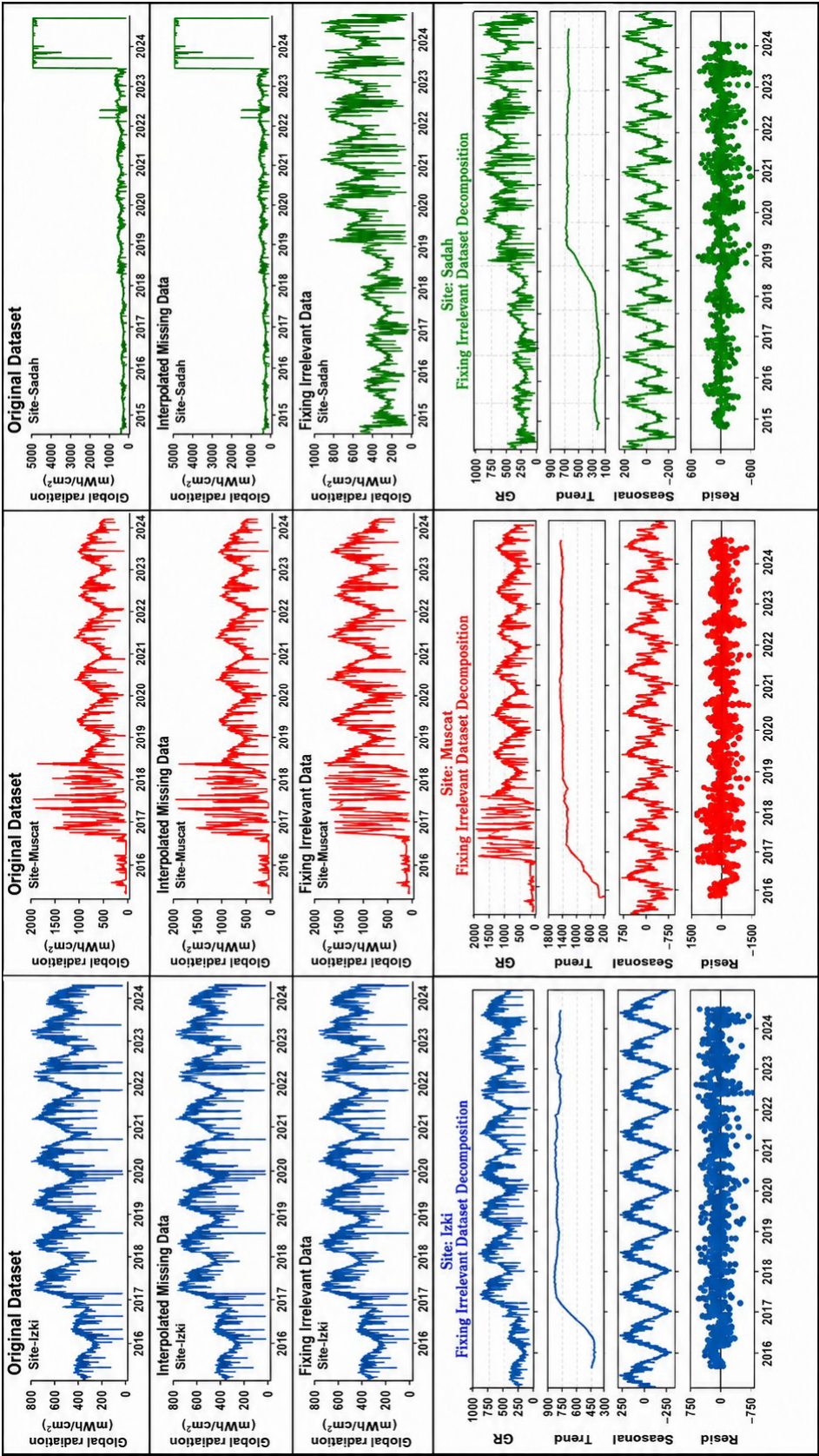


Figure 4. Global radiation dataset preprocessing: Imputing missing values, removing irrelevant datasets, and decomposing the dataset into linear trends, seasonal, and residual components
Abbreviation : GR: Global radiation.

(2017) and Voyant *et al.* (2017), such outlier values were removed or corrected using interpolation techniques to ensure temporal continuity.

In addition to handling outliers, null values in the GR variable were addressed through linear interpolation and forward/backward filling. These imputation strategies ensured the retention of long-term seasonal and trend components, which are vital for downstream forecasting tasks.

3.2.2. Chronological dataset splitting

To ensure temporal consistency and prevent information leakage, the dataset was split chronologically into training and testing sets. Data from 2014 to 2020 were used for training, while records from 2021 to 2024 were reserved for testing. This mirrored real-world forecasting applications, where models predict future values based solely on historical data. The total number of records and split ratios for each site are summarized in Table 3. For instance, Izki had 2,145 records in the training set and 1,461 in the testing set, while Sadah—due to missing 2024 data—had a slightly smaller test size. Table 3 shows that all three locations maintained high data coverage, with low missing values (< 0.1%), confirming the robustness of the dataset for long-term modeling applications.

Table 3. Chronological Dataset Splitting for Time-Series Forecasting Across Sites (Izki, Muscat, Sadah)

Year	Count			Dataset type	Dataset splitting
	Izki	Muscat	Sadah		
2014	–	–	258	Int64	Training
2015	318	207	365	Int64	Training
2016	366	366	366	Int64	Training
2017	365	365	365	Int64	Training
2018	365	365	365	Int64	Training
2019	365	365	365	Int64	Training
2020	366	366	366	Int64	Training
2021	365	365	365	Int64	Testing
2022	365	365	365	Int64	Testing
2023	365	365	228	Int64	Testing
2024	366	366	–	Int64	Testing
Training total	2,145 (59.5%)	2,034 (58.2%)	2,084 (61.2%)		
Testing total	1,461 (40.5%)	1,461 (41.8%)	1,324 (38.8%)		
Whole total	3,606	3,495	3,408		

3.2.3. Feature transformation and derivative construction

To prepare the dataset for forecasting, several transformation techniques were applied to the GR time series. These included first-order differencing (DiffGR) to eliminate trends, seasonal differencing (SDiffGR) to remove seasonal patterns, and logarithmic transformation (LogGR) to stabilize variance. A combined differenced-log transformation (DiffLogGR) was also computed to address both trend and heteroscedasticity simultaneously.

The resulting variables yielded multiple stationarized GR versions for different model architectures. Table 4 presents the non-null counts for each derived feature across the three sites. Although differencing and seasonal transformations naturally reduce the number of usable data points due to lag-based operations, all transformed variables retained more than 3,000 records per site, sufficient for training robust ML and DL models. For example, Izki's SDiffGR had 3,241 valid records out of 3606, indicating minimal data loss while achieving temporal normalization.

Table 4. Site-wise missing dates and data cleaning results

Site	Parameters	Counts	Null-count	Dataset type
Izki	GR	3,606	Non-null	Float64
	DiffGR	3,605	Non-null	Float64
	SDiffGR	3,241	Non-null	Float64
	LogGR	3,606	Non-null	Float64
	DiffLogGR	3,605	Non-null	Float64
Muscat	GR	3,495	Non-null	Float64
	DiffGR	3,494	Non-null	Float64
	SDiffGR	3,130	Non-null	Float64
	LogGR	3,495	Non-null	Float64
	DiffLogGR	3,494	Non-null	Float64
Sadah	GR	3,408	Non-null	Float64
	DiffGR	3,407	Non-null	Float64
	SDiffGR	3,043	Non-null	Float64
	LogGR	3,408	Non-null	Float64
	DiffLogGR	3,407	Non-null	Float64

Abbreviations: DiffGR: First-order differencing of global radiation; DiffLogGR: Combined differenced-log transformation of global radiation; GR: Global radiation; LogGR: Logarithmic transformation of global radiation; SDiffGR: Seasonal differencing of global radiation.

3.2.4. Stationarity testing and decomposition

Following the transformation, stationarity was assessed using the augmented Dickey–Fuller test and time-series decomposition. These procedures help confirm whether the statistical properties of the series—mean, variance, and autocorrelation—remain constant over time, a prerequisite for numerous forecasting models (Debnath & Mourshed, 2018; Yu *et al.*, 2019).

Decomposition results, as visualized in Figure 5, revealed strong seasonal components in GR across all sites, particularly annual cycles. The trend components showed a gradual increase in GR from 2016 to 2021, particularly in Muscat and Izki, while residual components were lowest in Izki, indicating more stable atmospheric conditions. In contrast, Sadah exhibited greater volatility in residuals, consistent with its higher variance in humidity and wind. Figure 5 demonstrates the entire preprocessing pipeline: from imputation of missing values and anomaly removal to decomposition into trend, seasonal, and residual components. These insights guided model selection and tuning in later phases.

3.3. Feature engineering and selection

Feature engineering is a fundamental process in ML-based forecasting, as the quality and representation of features directly influence model performance, especially in high-dimensional meteorological datasets. In this study, both temporal and meteorological features were systematically encoded and selected to enhance the predictive capability of regression models for long-term solar radiation forecasting across the three sites in Oman.

3.3.1. Feature encoding (day of the year, sin/cos transforms)

To capture the cyclical nature of solar radiation patterns, particularly their dependence on seasonal and diurnal cycles, time-based features such as day of the year (DOY) were encoded using sin and cos transformations. These transformations map the linear DOY values onto a unit circle, thereby preserving the cyclical structure and enabling models to better learn repeating seasonal patterns. The use of both sin (DOY) and cos (DOY) allows for the representation of periodic trends without introducing artificial discontinuities—such as the abrupt transition from December 31 to January 1—that are otherwise problematic in raw integer-based encodings. This technique is widely adopted in time series modeling, especially in energy forecasting, where solar insolation and temperature show clear seasonal variation (R. Ahmed *et al.*, 2020).

3.3.2. Feature selection

Once all relevant features were encoded, the dataset

underwent a feature selection process using multiple regression algorithms with default hyperparameter settings. These included models such as DTR, RFR, GBGR, and XGBR. The goal was to rank and identify the most influential predictors contributing to solar radiation variability across the study sites.

The importance scores generated by these regressors provided insights into which meteorological variables exerted the greatest influence on the target variable—GR. Commonly high-ranking features included latitude, SD, AT metrics (mean and max), and RH, particularly minimum RH, which showed a significant inverse relationship with solar radiation. These findings are consistent with existing literature that underscores the value of solar exposure, moisture content, and spatial attributes in driving solar PV output (Akhter *et al.*, 2019; Madeti & Singh, 2017b).

As illustrated in Figure 6, feature importance was extracted from multiple regression models, providing a visual comparison of how each algorithm prioritizes input variables. The redundancy and agreement across models served as an informal consensus to retain features that consistently contributed high importance scores.

Additionally, the feature selection process aided in dimensionality reduction, reducing the risk of overfitting while improving computational efficiency during model training. It also contributed to improved interpretability by narrowing down the model inputs to only the most physically and statistically meaningful features.

3.4. Model selection

We integrated traditional ML models and DL architectures to predict solar radiation, aiming to capture both linear and nonlinear patterns in the meteorological data. The selected ML models include MLR, which served as a baseline due to its simplicity and interpretability when modeling linear relationships (Pazikadin *et al.*, 2020). DTR, which is critical for handling complex datasets (Alzahrani *et al.*, 2017), was employed to capture nonlinear interactions between features. RFR, an ensemble learning method, aggregates predictions from multiple decision trees, thus reducing overfitting and improving robustness (H. Wang *et al.*, 2019). GBR and XGBR are advanced ensemble techniques that build trees sequentially to correct the errors of previous models, making them highly effective in handling noisy, high-dimensional data (Das *et al.*, 2018; van der Meer *et al.*, 2018). Additionally, ER aggregates the best-performing base models to enhance predictive accuracy and reduce bias, leveraging the strengths of multiple algorithms (Kumar *et al.*, 2020). On the DL side, LSTM networks are employed due to their ability to capture long-term dependencies in sequential data, an essential feature

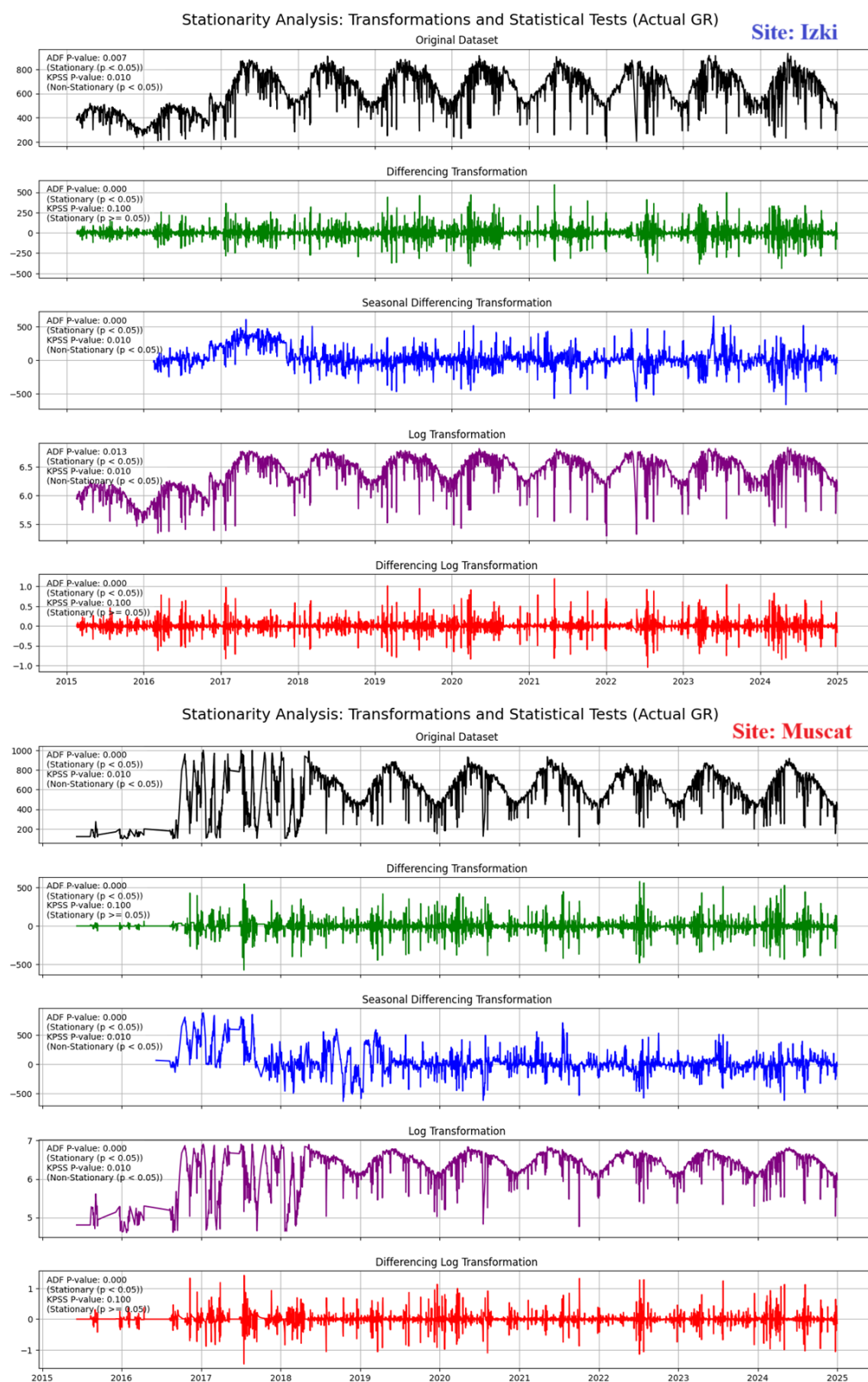


Figure 5. Stationarity test results across different sites

Abbreviations: ADF: Augmented Dickey–Fuller; KPSS: Kwiatkowski–Phillips–Schmidt–Shin test.

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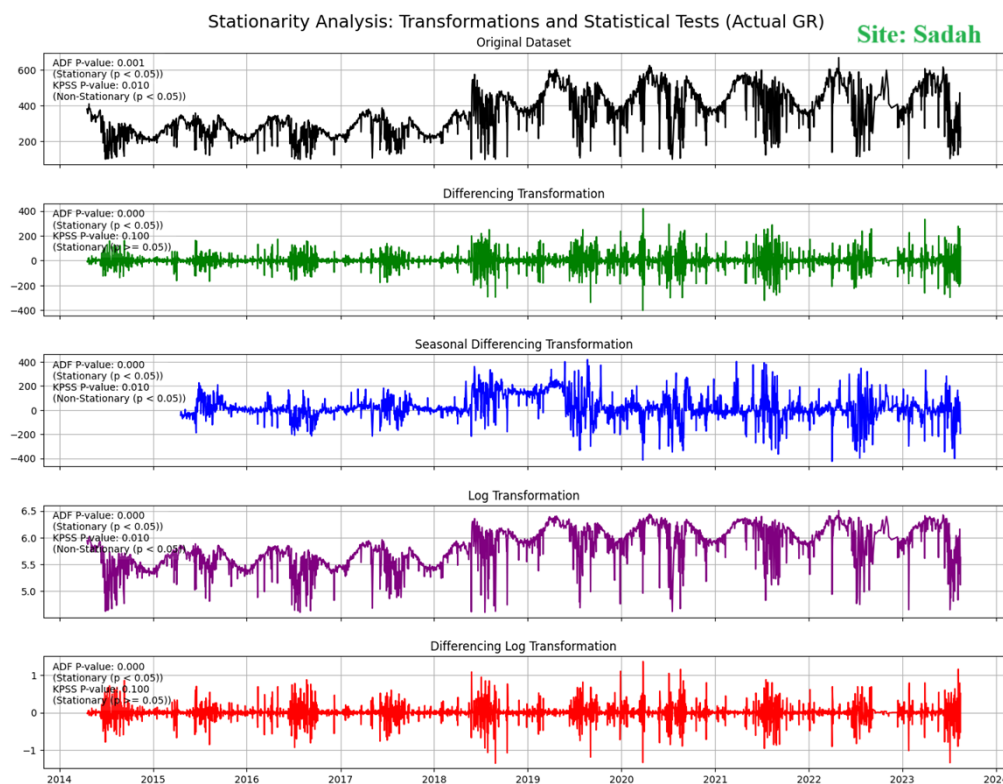


Figure 5. Continued

for time-series forecasting (Notton *et al.*, 2018). CNNs are incorporated to detect local patterns in the data, enhancing the model's ability to capture short-term fluctuations in solar radiation (F. Wang *et al.*, 2020). A Hybrid LSTM + CNN model is used to combine both approaches, allowing the model to learn both long-term temporal dependencies and local spatial patterns simultaneously, a strategy that has shown promise in time-series forecasting applications (Koprinska *et al.*, 2018).

3.5. Model training and evaluation

In this study, models were trained using data from 2014 to 2020, with performance evaluated on data from 2021 to 2024. The training process included hyperparameter tuning using grid search, which tests different combinations of parameters to optimize model performance (Koprinska *et al.*, 2018). Cross-validation was applied to assess the models' generalizability and to prevent overfitting by training the models on multiple subsets of the data (F. Wang *et al.*, 2019). The models were evaluated using several performance metrics: Coefficient of determination

(R^2) measures the proportion of variance explained by the model, with higher values indicating better performance (Yap *et al.*, 2020); mean squared error (MSE) calculates the average squared difference between predicted and actual values, penalizing larger errors more heavily (F. Wang *et al.*, 2020); root mean squared error (RMSE) provides an interpretable measure of error in the same units as the original data (Mellit & Kalogirou, 2008); and mean absolute percentage error (MAPE) expresses prediction error as a percentage of actual values, useful for comparing models across different scales (Jung *et al.*, 2020). A sensitivity analysis was conducted to assess the models' robustness by varying parameters, including random seeds and test sizes. This analysis ensured that the models' performance remained stable and reliable under different conditions (F. Wang *et al.*, 2020). To enhance model interpretability, Shapley additive explanations (SHAP) values were used to explain the contribution of each feature to individual predictions, offering insights into how different features influence the model's output (Hossain *et al.*, 2019). Partial dependence plots (PDPs) were also utilized to visualize the

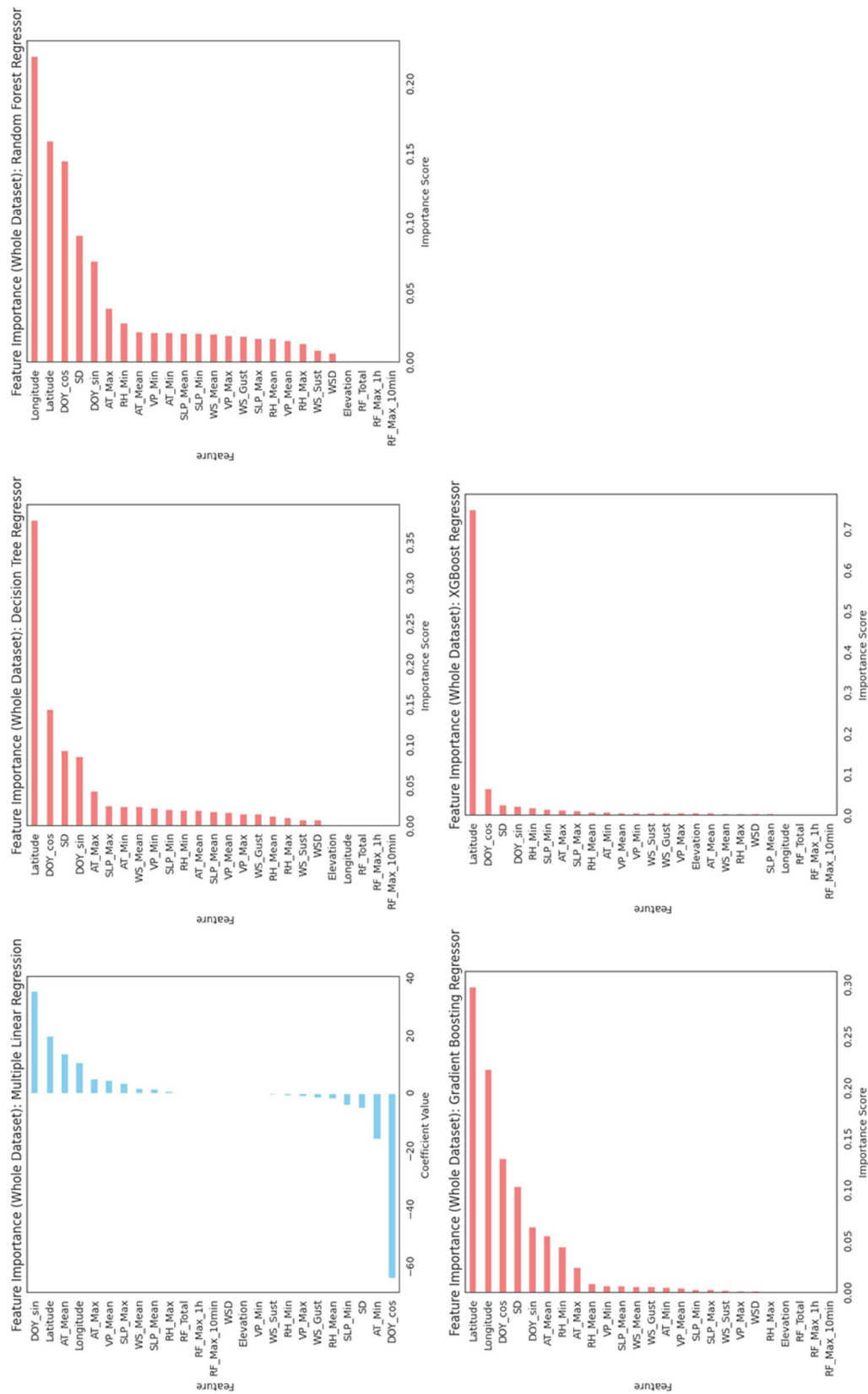


Figure 6. Extract important features by running various regression algorithms with their default hyperparameter settings
Abbreviations: AT: Air temperature; DOY: Day of the year; RF: Rainfall; RH: Relative humidity; SD: Sunshine duration; SLP: Station-level pressure; VP: Vapor pressure; WS: Wind speed; WSD: Wind direction.

relationships between input features and predicted solar radiation values, helping to identify nonlinear patterns in the data (F. Wang *et al.*, 2020).

3.6. Model comparison

A comparative analysis was performed between the ML and DL models to evaluate their respective performance in solar radiation forecasting. The ensemble ML models, such as ER and RFR, excelled in short-term forecasting due to their ability to reduce overfitting and their robustness in handling noisy data (Huang & Kuo, 2019; Motahhir *et al.*, 2020). These models demonstrated high accuracy when predicting solar radiation in the short term, where they could rely on the most recent trends and patterns. However, in long-term forecasting, DL models, particularly the LSTM + CNN hybrid, outperformed the ML models. The LSTM + CNN hybrid effectively captured both long-term temporal dependencies (through LSTM) and local short-term patterns (through CNN), which are essential for long-term solar radiation forecasting (Nishant *et al.*, 2020). The hybrid model's ability to integrate spatial and temporal features allowed it to maintain superior performance across multiple seasons, making it more suitable for long-term predictions in dynamic and seasonal environments, as opposed to traditional ML methods, which often struggled with such complexities (Hossain *et al.*, 2019; Kumar *et al.*, 2020). This hybrid approach demonstrated greater generalization and stability over extended forecasting horizons, underscoring its potential for accurate solar PV prediction in Oman's diverse climatic zones.

4. Results

This section presents the performance evaluation and comparative analysis of the developed forecasting models for long-term solar radiation prediction. The results were analyzed using multiple statistical metrics, sensitivity analysis, and explainability techniques to assess model accuracy, robustness, and forecasting capability across different climatic regions in Oman.

4.1. Machine learning-based prediction modeling

This subsection focuses on the implementation and evaluation of ML models used for solar forecasting. Different regression algorithms were investigated to determine their ability to capture nonlinear relationships between meteorological variables and solar radiation while maintaining predictive stability over long forecasting horizons.

4.1.1. Model selection

To effectively predict solar radiation from multivariate meteorological data, six regression algorithms were

employed: MLR, DTR, RFR, GBR, XGBR, and an ER combining the best-performing models. The selection was based on their proven capabilities in previous solar forecasting and environmental modeling studies (Alotaibi *et al.*, 2020; Antonanzas *et al.*, 2016; Huang & Kuo, 2019).

The MLR served as a benchmark linear approach, while tree-based algorithms like DTR and RFR captured nonlinearities and feature interactions. Boosting methods such as GBR and XGBR were included due to their superior performance in high-dimensional and noisy datasets. Finally, ER aggregated predictions to exploit complementary strengths and reduce model bias and variance (F. Wang *et al.*, 2020). These models provide a range of complexity and interpretability, suitable for evaluating the trade-offs in long-term solar energy forecasting.

4.1.2. Hyperparameter tuning

Table 5 outlines the grid search results and optimal hyperparameters for each ML model. The tuning process involved exhaustive parameter search across key dimensions (e.g., tree depth, learning rate, number of estimators). For instance, the RFR achieved optimal performance with 300 estimators, max depth of 30, and bootstrap = True, resulting in a training R^2 of 0.96 and validation R^2 of 0.78. Similarly, XGBR achieved its best performance with a low learning rate (0.01), deep tree structure (depth = 10), and subsample ratio of 0.6. The choice of learning rate and tree depth plays a critical role in preventing overfitting and improving generalizability (Mellit & Kalogirou, 2008; Nishant *et al.*, 2020).

The MLR required no tuning due to its parametric nature. The improvements demonstrated by ensemble models after tuning confirm the importance of careful hyperparameter optimization for performance maximization.

4.1.3. Sensitivity analysis

Sensitivity analysis was conducted to assess the models' robustness against random seed values and test sizes, as reported in Table 6 and illustrated in Figure 7. Ensemble methods (especially XGBR and ER) demonstrated lower variability and higher performance across different configurations. The ER model achieved the highest validation R^2 of 0.83, proving to be the most stable across data split changes. In contrast, simpler models such as MLR and DTR showed higher sensitivity but lower stability, reflecting their limited ability to capture the complex dynamics of atmospheric data. This experiment supports findings from recent solar forecasting literature, which highlight the effectiveness of ensemble methods in generalizing across multiple scenarios (Ghimire *et al.*, 2019; D. Yang *et al.*, 2018).

Table 5. Grid search results and optimal parameters per model

Regression algorithm	Hyper parameters	Test range	Optimized parameter	Best train R^2	Best validation R^2
MLR	–	–	–	–	–
DTR	‘max_depth’	[None, 5, 10, 20, 30]	10	0.79	0.71
	‘min_samples_split’	[2, 5, 10, 20]	2		
	‘min_samples_leaf’	[1, 2, 4, 8, 16]	8		
	‘max_features’	[None, ‘sqrt,’ ‘log2,’ 0.5, 0.8]	0.8		
	‘criterion’	[‘squared_error,’ ‘friedman_mse,’ ‘absolute_error’]	‘squared_error’		
RFR	‘n_estimators’	[50, 100, 200, 300]	300	0.96	0.78
	‘max_depth’	[None, 10, 20, 30]	30		
	‘min_samples_split’	[2, 5, 10]	2		
	‘min_samples_leaf’	[1, 2, 4]	1		
	‘max_features’	[‘sqrt,’ ‘log2,’ None]	None		
	‘bootstrap’	[True, false]	True		
GBR	‘n_estimators’	[100, 200, 300]	200	0.88	0.77
	‘max_depth’	[3, 5, 7]	7		
	‘min_samples_split’	[2, 5, 10]	2		
	‘min_samples_leaf’	[1, 3, 5]	5		
	‘max_features’	[‘sqrt,’ ‘log2,’ None]	None		
	‘subsample’	[0.8, 1.0]	0.8		
	‘learning_rate’	[0.05, 0.1, 0.15]	0.05		
XGBR	‘n_estimators’	[100, 200, 300]	300	0.87	0.78
	‘learning_rate’	[0.01, 0.05, 0.1, 0.2]	0.01		
	‘max_depth’	[3, 5, 7, 10]	10		
	‘subsample’	[0.6, 0.8, 1.0]	0.6		
	‘colsample_bytree’	[0.6, 0.8, 1.0]	1.0		
	‘gamma’	[0, 0.1, 0.5, 1]	0.1		
	‘min_child_weight’	[1, 5, 10]	5		

Abbreviations: DTR: Decision tree regressor; GBR: Gradient boosting regressor; MLR: Multiple linear regression; RFR: Random forest regressor; XGBR: Extreme gradient boosting regressor.

4.1.4. Performance evaluation

Model performance was rigorously assessed using standard regression metrics—MSE, RMSE, MAPE, and the R^2 —as summarized in Table 7. Among all models, the ER approach demonstrated the highest predictive accuracy, achieving a validation R^2 score of 0.96, an RMSE of 38.60, and an MAPE of 6.16%, outperforming all individual models. RFR and XGBR also showed robust performance (both $R^2 = 0.78$), though RFR yielded a slightly higher validation error. In contrast, the MLR baseline, while interpretable and computationally simple, yielded the weakest validation performance ($R^2 = 0.65$), failing to capture the complex nonlinear dependencies inherent in

meteorological data. These results are visually reinforced in Figure 8, which plots actual vs. predicted solar radiation values for each model. The ER model's predictions were tightly clustered along the ideal 1:1 line, indicating high fidelity and generalization. In contrast, models such as MLR and DTR exhibited scattered predictions, likely due to underfitting or overfitting. These findings support existing literature that favors ensemble and tree-based approaches for solar radiation forecasting due to their superior ability to capture nonlinear interactions among predictors (Antonanzas *et al.*, 2016; Kumar *et al.*, 2020; Shamshirband *et al.*, 2019; Sobri *et al.*, 2018). Overall, the results validate the effectiveness of advanced ML models in high-dimensional, real-world energy forecasting scenarios.

Table 6. Model sensitivity to random seed and test size

Regression algorithm	Datasets sensitive parameter		
	Random state (1–100)	Test size (0.10–0.25)	Best R2
Multiple linear regression (MLR)	32	0.1	0.65
Decision tree regression (DTR)	62	0.1	0.64
Random forest regression (RFR)	53	0.1	0.78
Gradient boosting regression (GBR)	43	0.1	0.71
Extreme gradient boosting regression (XGBR)	78	0.1	0.76
Ensemble regression (ER)	78	0.1	0.83

Table 7. Performance metrics for all machine learning models (train and validation)

Site	Training					Validation			
	Accuracy	MSE	RMSE	MAPE	R^2	MSE	RMSE	MAPE	R^2
MLR	56.97 ± 2.17	16,994.71	130.36	24.39	0.57	13,402.39	115.77	21.68	0.65
DTR	66.93 ± 3.47	8,105.28	90.03	14.55	0.79	12,028.97	109.68	16.73	0.71
RFR	73.79 ± 1.70	1,404.11	37.47	6.13	0.96	9,083.39	95.31	17.14	0.78
GBR	73.29 ± 2.02	4,838.14	69.56	12.02	0.88	8,850.22	94.08	16.10	0.77
XGBR	73.07 ± 1.64	5,185.92	72.01	12.86	0.87	8,798.66	93.80	16.77	0.78
Ensemble	74.42 ± 0.01	3,443.18	58.67	10.22	0.91	1,490.04	38.60	6.16	0.96

Abbreviations: DTR: Decision tree regressor; GBR: Gradient boosting regressor; MAPE: Mean absolute percentage error; MLR: Multiple linear regression; MSE: Mean squared error; RFR: Random forest regressor; RMSE: Root mean squared error; XGBR: Extreme gradient boosting regressor.

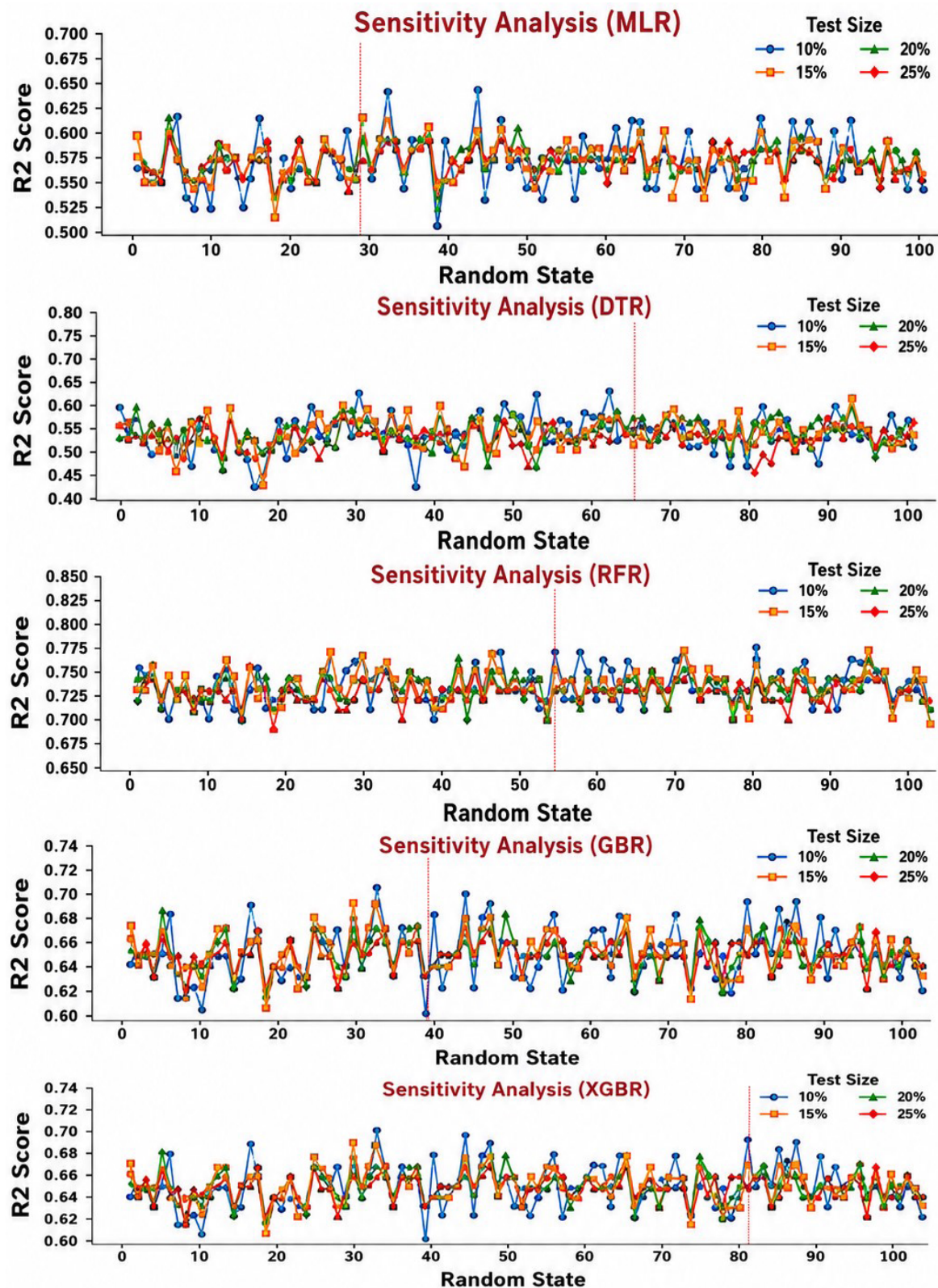


Figure 7. Sensitivity analysis

Abbreviations: DTR: Decision tree regressor; GBR: Gradient boosting regressor; MLR: Multiple linear regression; RFR: Random forest regressor; XGBR: Extreme gradient boosting regressor.

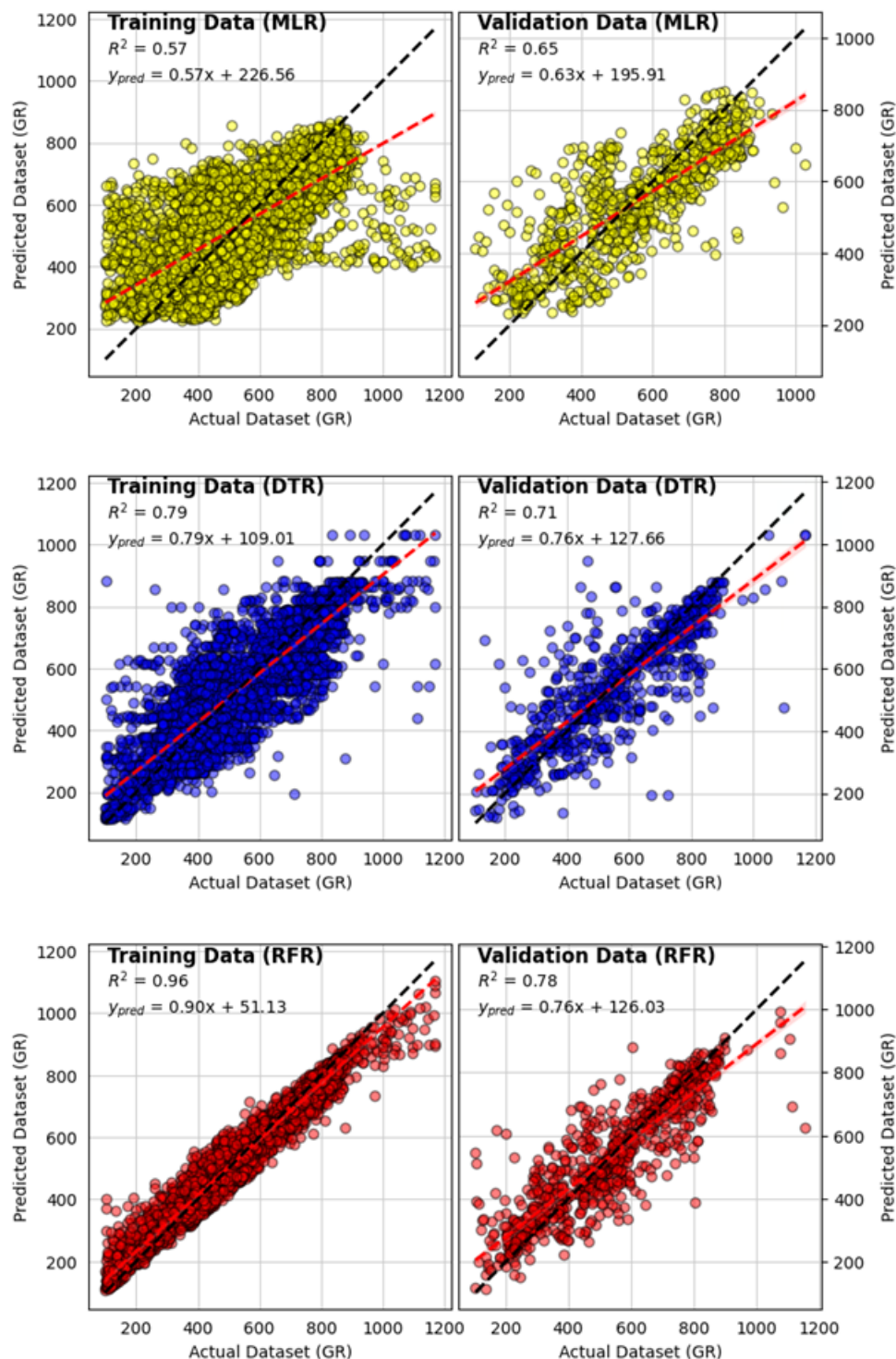


Figure 8. Comparison between actual and predicted values (machine learning models)

Abbreviations: DTR: Decision tree regressor; GBR: Gradient boosting regressor; GR: Global radiation; MLR: Multiple linear regression; RFR: Random forest regressor; XGBR: Extreme gradient boosting regressor.

(Cont'd...)

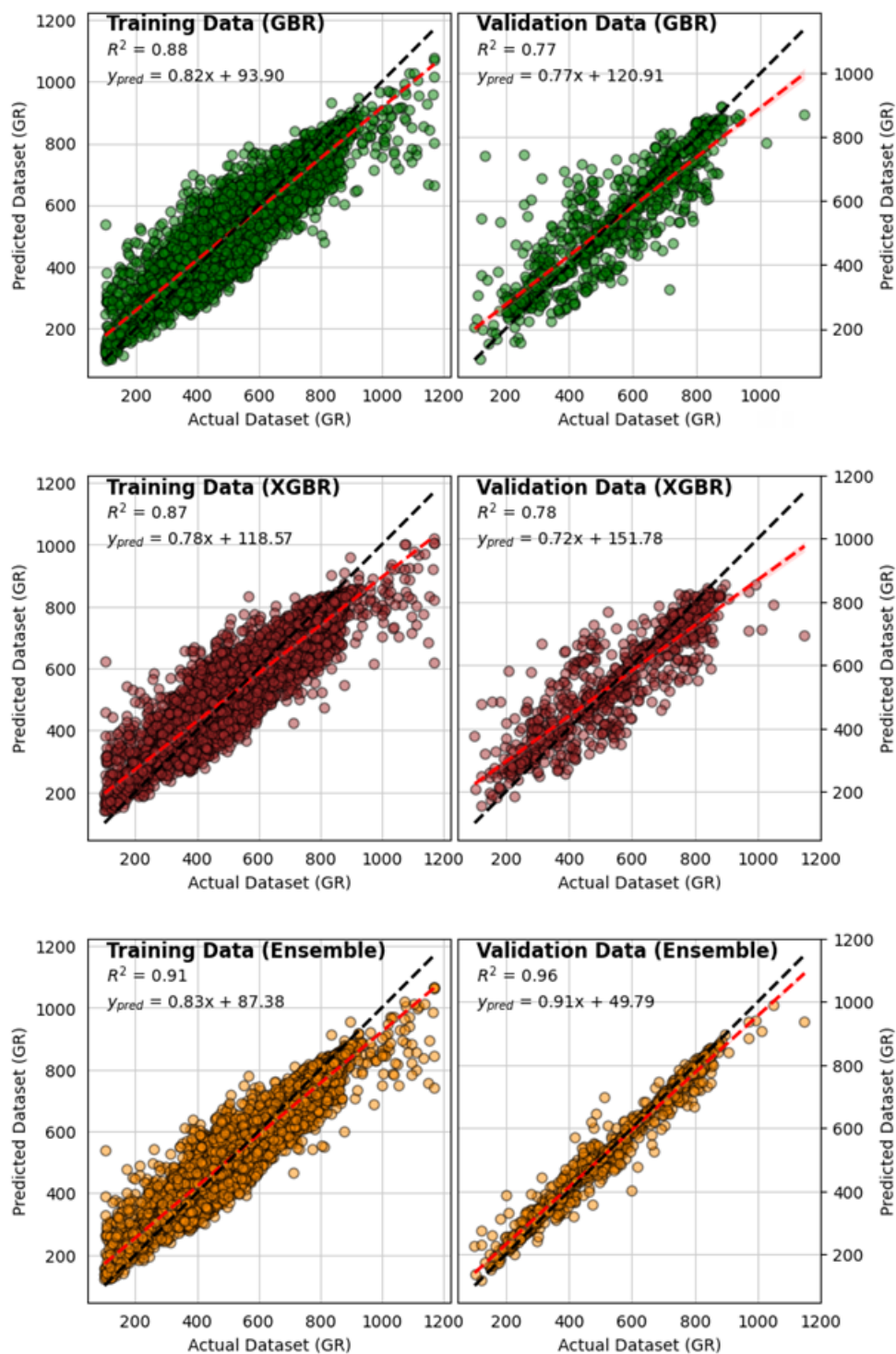


Figure 8. Continued

4.1.5. Post-prediction modeling evaluation parameter

To improve model interpretability and understand the influence of input variables on solar radiation forecasting, post-prediction evaluation techniques were employed. SHAP and PDPs were used to identify important features, analyze their contributions, and enhance the transparency and reliability of the proposed ML framework.

- (i) Shapley additive explanations-based feature importance

To interpret the ML model's predictions and understand the influence of each input variable on solar radiation output, SHAP analysis was employed. SHAP values quantify the contribution of each feature to individual predictions and help uncover complex, nonlinear relationships inherent in meteorological datasets (Koprinska *et al.*, 2018). As shown in Figure 9, the SHAP summary plot displays the

distribution of SHAP values across the top eight predictive features. Each dot represents a single observation, color-coded by feature value, indicating whether higher or lower values increase or decrease model output. The features latitude, DOY_cos (cosine-transformed day of the year), and longitude exert the highest impact on the predicted solar radiation. These geospatial and seasonal indicators strongly influence solar availability.

Furthermore, Figure 10 ranks features by their mean absolute SHAP values, reinforcing the dominance of spatial and temporal variables. Latitude had the highest mean SHAP impact (+61.25), followed by DOY_cos (+50.43) and longitude (+37.41). Meteorological parameters such as SD, minimum RH (RH_Min), and AT (AT_Max, AT_Mean) also contributed meaningfully but to a lesser extent. These findings highlight the value of SHAP in identifying feature importance and guiding reliable solar PV prediction.

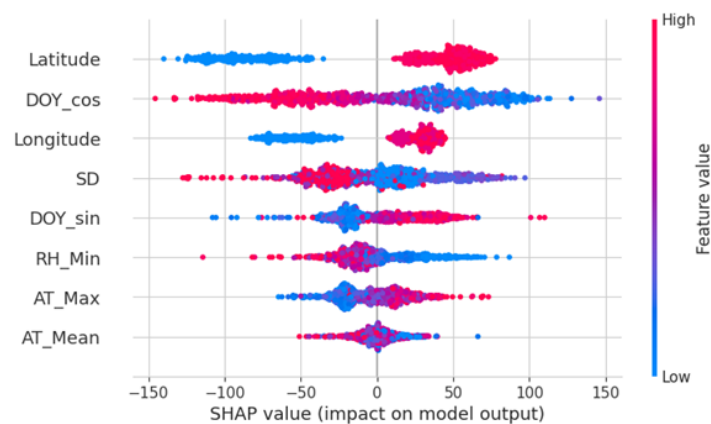


Figure 9. SHAP summary plot illustrating the impact of key features on the machine learning model's output for solar photovoltaic power prediction. Abbreviations: AT: Air temperature; DOY: Day of the year; RH: Relative humidity; SD: Sunshine duration; SHAP: Shapley additive explanations.

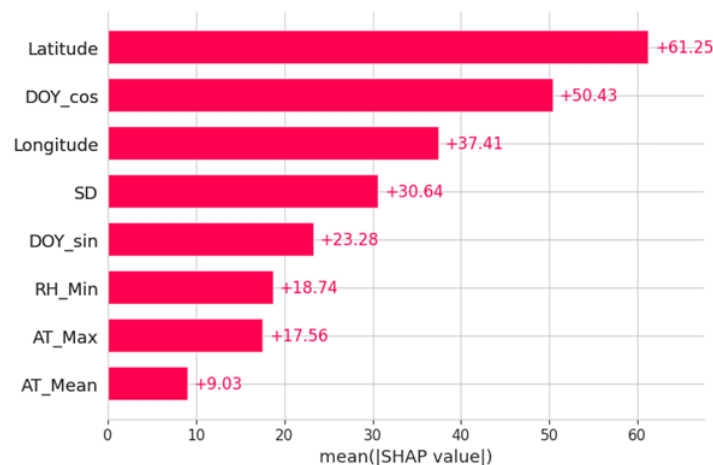


Figure 10. Mean SHAP values for top features

Abbreviations: AT: Air temperature; DOY: Day of the year; RH: Relative humidity; SD: Sunshine duration; SHAP: Shapley additive explanations.

(ii) Partial dependency plot

The PDP was employed to investigate the marginal effect of individual input features on the predicted solar radiation output, while keeping all other features constant. As illustrated in Figure 11, PDPs reveal the nature and strength of the relationship between specific predictors and the model response, enabling detection of nonlinear behaviors and threshold effects. Notably, SD demonstrated a strong positive association with GR, with increasing SD values corresponding to higher GR predictions up to a saturation point, beyond which the incremental gains diminished. Likewise, maximum AT (AT_Max) showed a generally positive trend with GR, although the relationship flattened at higher temperatures, suggesting a potential plateau in solar radiation response. These observations highlight important nonlinear dependencies and inflection points in the data, offering valuable insights into the physical dynamics captured by the model and enhancing its interpretability in practical solar energy forecasting scenarios.

4.2. Deep learning-based forecasting modeling

4.2.1. Data preparation for forecasting

The data used in the DL models followed the same 10-year historical sequence as the ML section, comprising daily observations from Izki, Muscat, and Sadah. To prepare the data for sequential forecasting, a sliding-window approach was used with a fixed input sequence length of 100 days. This sequence was used to predict a future target horizon of GR. All features were normalized using min–max scaling, and missing values were handled using forward-fill interpolation as described in Section 3. For

models incorporating exogenous variables, additional meteorological inputs such as SD, vapor pressure, temperature, and humidity were appended to the input tensor. Data splitting respected temporal order: records from 2014–2020 were used for training, and data from 2021 onward for testing, ensuring that future information was not leaked into the training phase. The careful design of the input structure helped mitigate overfitting and improve the model's generalization across multiple seasonal cycles.

4.2.2. Forecasting models and architectures

The study deployed a diverse range of forecasting architectures to model GR, highlighting an evolution from traditional sequential models to advanced hybrid DL systems, as detailed in Table 8. The foundational LSTM (one-step) model, though the parameter count was not specified, comprised a single LSTM layer followed by a dense layer and served as a baseline for single-horizon predictions. Enhanced performance was observed in the LSTM (multi-step) model with three stacked LSTM layers and 23,991 parameters, designed to capture deeper temporal dependencies, consistent with findings from Vanegas Cantarero (2020), who demonstrated the effectiveness of deep LSTM architectures in solar radiation forecasting. Meanwhile, CNN-based models such as the CNN (multi-step) and CNN (sequence-to-sequence [Seq2Seq]) incorporated one and two one-dimensional convolution layers, respectively, with corresponding complexities of 1,718,151 and 3,381,639 parameters. These were instrumental in detecting local temporal patterns, aligning with the work of Alotaibi *et al.* (2020), which emphasized the utility of CNNs for time series prediction despite their lack of long-term memory. To bridge this

Table 8. The model architecture of various models used for time-series forecasting of global radiation

No	Forecasting model	Input sequence length	Model layers	Total parameters
1	LSTM (one-step)	100	LSTM (1) + dense	Not specified
2	LSTM (multi-step)	100	LSTM (3) + dense	23,991
3	CNN (multi-step)	100	Conv1D (1) + pool + flatten + dense	1,718,151
4	CNN (Seq2Seq)	100	Conv1D (2) + pool + flatten + dense	3,381,639
5	LSTM + CNN (Seq2Seq)	100	Conv1D (2) + pool + LSTM (2) + dense	268,871
6	LSTM + CNN (recursive)	100	Conv1D (2) + pool + LSTM (2) + dense	197,761
7	LSTM + CNN (recursive + exogenous)	100	Conv1D (2) + pool + LSTM (2) + dense	Not specified
8	LSTM + CNN (recursive on residuals)	100	Conv1D (2) + pool + LSTM (2) + dense	Not specified
9	Prophet (baseline)	–	Additive model (trend + seasonality + holidays)	~20 (internal)

Abbreviations: CNN: Convolutional neural network; Conv1D: One-dimensional convolution; LSTM: Long short-term memory.

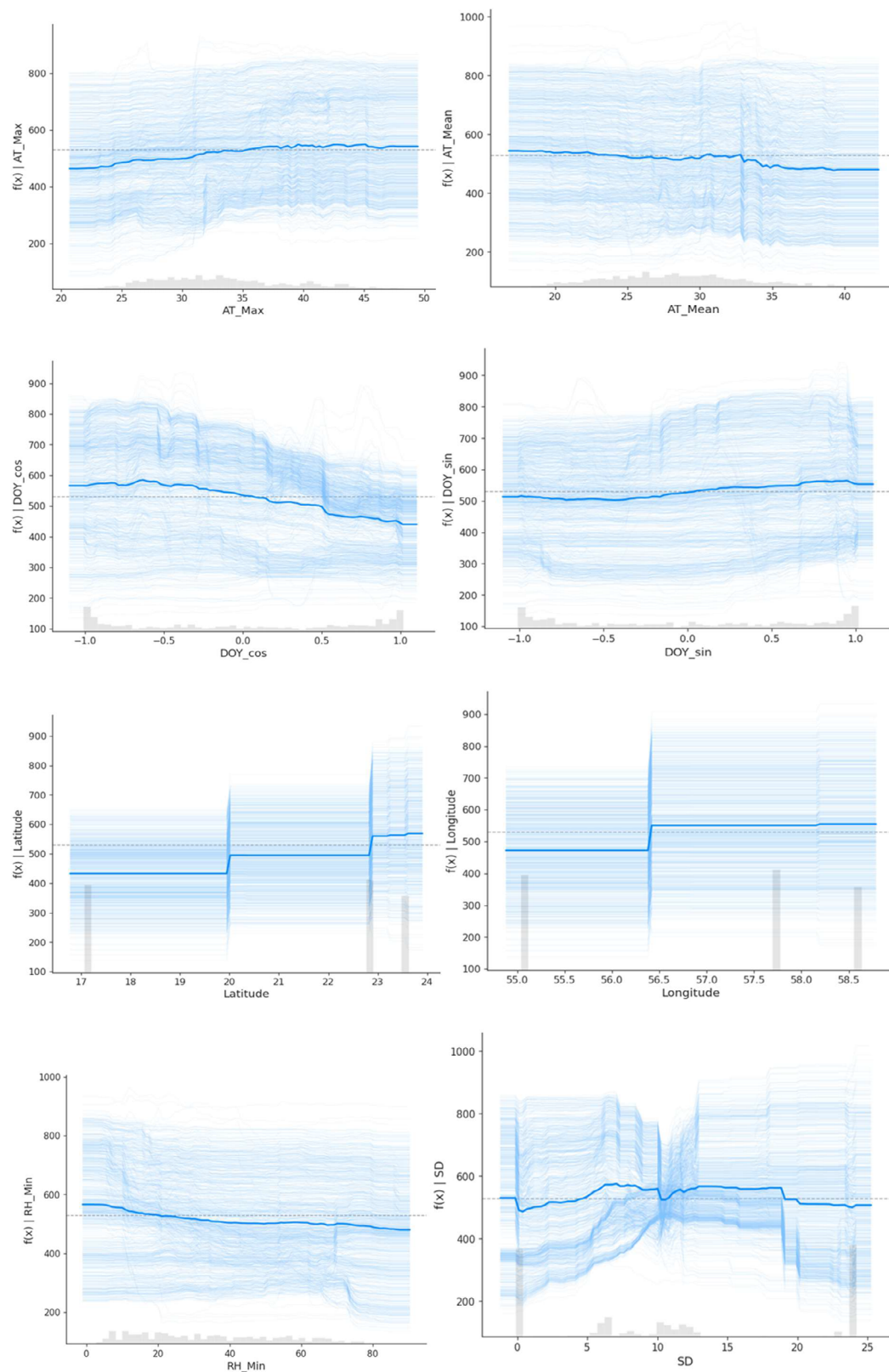


Figure 11. Partial dependence plot

Abbreviations: AT: Air temperature; DOY: Day of the year; RH: Relative humidity; SD: Sunshine duration.

gap, hybrid models such as LSTM + CNN (Seq2Seq) and LSTM + CNN (recursive) were introduced, integrating convolutional and LSTM layers to simultaneously learn spatial and temporal patterns, with parameter counts of 268,871 and 197,761, respectively. These hybrid approaches are supported by Nishant *et al.* (2020), who showed that combining CNNs and RNNs enhances multivariate sequence modeling. Further sophistication was achieved through LSTM + CNN (recursive with exogenous features) and LSTM + CNN (recursive on residuals) models. Although their parameter counts were not explicitly stated, these models incorporated auxiliary inputs (e.g., humidity, SD) and recursive residual learning, which significantly improved long-term forecast stability—echoing the findings of Alotaibi *et al.* (2020) on residual-enhanced DL. For benchmark comparison, the Prophet model (Koprinska *et al.*, 2018; Notton *et al.*, 2018), a lightweight additive framework with ~20 internal parameters, was included. While it offers interpretability through decomposed seasonality and trend components, its limited capacity to handle nonlinear dependencies makes it less suitable for complex GR forecasting. Overall, this architectural spectrum—from shallow models to parameter-optimized hybrid networks—demonstrates a clear progression in model sophistication, addressing the challenges of nonstationarity, seasonality, and exogenous influence inherent in solar radiation time series across diverse Omani climates.

4.2.3. Forecasting performance

The performance evaluation of various DL architectures for long-term solar radiation forecasting was conducted using metrics such as MAE, loss, and validation loss across three key locations in Oman—Izki, Muscat, and Sadah. As presented in Table 9, the hybrid LSTM + CNN (recursive forecasting on residuals) model consistently outperformed all other architectures across all sites in terms of accuracy and error minimization.

At Izki, this model achieved the lowest validation MAE of 0.1421 with a training MAE of only 0.0119 and a validation loss of 0.0455, indicating strong generalization and minimal overfitting. Similarly, for Muscat, the validation MAE was 0.1509, and for Sadah, which exhibited more volatile meteorological conditions, the model still maintained a competitive validation MAE of 0.1740. These results demonstrate the robustness of the residual learning approach, which captures unexplained variance and corrects model outputs over iterative sequences.

In comparison, simpler architectures such as the LSTM (one-step) and CNN (multi-step) showed higher validation MAE values. For instance, the LSTM (One-Step) yielded 0.0870 at Izki and substantially worse performance at

Sadah (0.1165), highlighting its limited ability to handle longer-term dependencies and atmospheric variability. Models using multi-step forecasting (e.g., LSTM + CNN Seq2Seq) performed moderately better but were still surpassed by recursive models, particularly when combined with residual correction or exogenous features (e.g., SD, humidity).

Visual comparisons in Figure 12 further illustrate the superior forecasting ability of the LSTM + CNN (recursive on residuals) model, showing stable three-year predictions beyond 2025 for Izki and Muscat, and beyond 2024 for Sadah. In contrast, Figure 13 presents the forecast produced by the Prophet model, a baseline statistical approach. While Prophet models showed reasonable seasonal tracking, they lacked the precision and adaptability of DL models, particularly under high-variance conditions such as those in Sadah.

These findings are consistent with prior research, which emphasizes the value of hybrid DL and residual learning techniques in solar energy forecasting (Motahhir *et al.*, 2020; Notton *et al.*, 2018). Recursive architectures, especially those augmented with residual forecasting mechanisms, effectively reduce cumulative error and enhance temporal stability, making them particularly suitable for long-horizon prediction tasks in dynamic climate environments like Oman.

4.3. Comparative evaluation

4.3.1. Machine learning vs. deep learning: Accuracy and robustness

The comparative analysis of ML and DL models revealed distinct differences in predictive performance and robustness for long-term solar radiation forecasting. Among the ML models tested, the ER achieved the highest validation accuracy, with an R^2 of 0.96 and an RMSE of 38.60, outperforming individual regressors such as RFR ($R^2 = 0.78$, RMSE = 95.31) and XGBR ($R^2 = 0.78$, RMSE = 93.80). These results are consistent with previous literature emphasizing the robustness of ensemble methods for environmental forecasting tasks (Mellit & Kalogirou, 2008; Nishant *et al.*, 2020), owing to their ability to reduce model bias and variance through aggregation techniques.

In contrast, DL models, particularly the LSTM + CNN (recursive forecasting on residuals) architecture, demonstrated superior performance in long-range temporal prediction tasks. While slightly lower in short-term R^2 (0.85–0.88 inferred), the model achieved notably low validation MAE values: 0.1421 for Izki, 0.1509 for Muscat, and 0.1740 for Sadah. These results illustrate the model's capacity to capture temporal dependencies and correct residual forecast errors through recursive residual

Table 9. Performance evaluation of various models based on mean absolute error, overall loss for both training and validation datasets

Algorithm	Site	Epoch	Loss	MAE	Val_loss	Val_MAE
1. LSTM (one-Step)–algorithm	Izki	50	0.0158	0.0763	0.0228	0.0870
	Muscat	50	0.0334	0.1011	0.0290	0.0869
	Sadah	50	0.0319	0.1029	0.0430	0.1165
2. LSTM (multi-Step)–algorithm	Izki	50	0.0205	0.0789	0.0262	0.0850
	Muscat	50	0.0436	0.1114	0.0365	0.0929
	Sadah	50	0.0361	0.1036	0.0467	0.1164
3. CNN (multi-step)–algorithm	Izki	50	0.0206	0.0791	0.0262	0.0851
	Muscat	50	0.0437	0.1116	0.0365	0.0930
	Sadah	50	0.0364	0.1040	0.0468	0.1167
4. CNN (multi-step) (sequence-to-sequence forecasting)–algorithm	Izki	100	0.0206	0.0789	0.0262	0.0851
	Muscat	100	0.0436	0.1116	0.0365	0.0932
	Sadah	100	0.0363	0.1039	0.0468	0.1169
5. LSTM + CNN (multi-step) (sequence-to-sequence forecasting)–algorithm	Izki	200	0.0172	0.0830	0.0287	0.1000
	Muscat	200	0.0348	0.1203	0.0424	0.1239
	Sadah	200	0.0292	0.1101	0.0533	0.1457
6. LSTM + CNN (multi-step) (recursive forecasting)–algorithm	Izki	200	4.4×10^{-4}	0.0153	0.0392	0.1308
	Muscat	200	5.8×10^{-4}	0.0169	0.0532	0.1408
	Sadah	200	3.2×10^{-4}	0.0136	0.0712	0.1715
7. LSTM + CNN (multi-step) (recursive forecasting with exogenous features)–algorithm	Izki	200	5.5×10^{-4}	0.0173	0.0361	0.1267
	Muscat	200	0.0017	0.0288	0.0600	0.1479
	Sadah	200	0.0012	0.0251	0.0779	0.1881
8. LSTM + CNN (multi-step) (recursive forecasting on residuals)–algorithm	Izki	200	2.4×10^{-4}	0.0119	0.0455	0.1421
	Muscat	200	6.2×10^{-4}	0.0187	0.0469	0.1509
	Sadah	200	0.0014	0.0272	0.0695	0.1740

Abbreviations: CNN: Convolutional neural network; LSTM: Long short-term memory; MAE: Mean absolute error; Val: Validation.

learning—a finding that aligns with Vanegas Cantarero (2020), who advocated hybrid LSTM-CNN architectures in solar energy time-series forecasting due to their capacity to learn both spatial and sequential features.

Overall, while ML models like ER excel in predictive accuracy for near-term horizons, DL models exhibit greater robustness and stability over extended forecast periods, especially under conditions of climatic variability.

4.3.2. Site-wise model performance differences

Performance analysis across the three study locations—Izki, Muscat, and Sadah—highlighted the influence of local meteorological variability on model accuracy. Izki, with relatively stable climatic conditions and moderate solar radiation (mean GR = 465.72 ± 128.45 mWh/cm²),

consistently produced the lowest prediction errors across both ML and DL models. For example, the LSTM + CNN (recursive on residuals) achieved a training MAE of 0.0119 and a validation MAE of 0.1421 at this site.

Muscat, which features the highest average solar radiation (487.39 ± 135.87 mWh/cm²) and SD (10.35 ± 2.43 hours/day), also yielded strong forecasting results, though it showed slightly higher variability in DL model training loss. Meanwhile, Sadah, characterized by elevated wind speeds (3.02 ± 1.35 m/s) and rainfall (4.85 ± 8.22 mm), posed the greatest challenge for both model types. All models exhibited higher MAE and RMSE values in Sadah, emphasizing the impact of geographic heterogeneity and atmospheric volatility on forecast reliability. These findings align with an earlier study by Antonanzas *et al.* (2016),

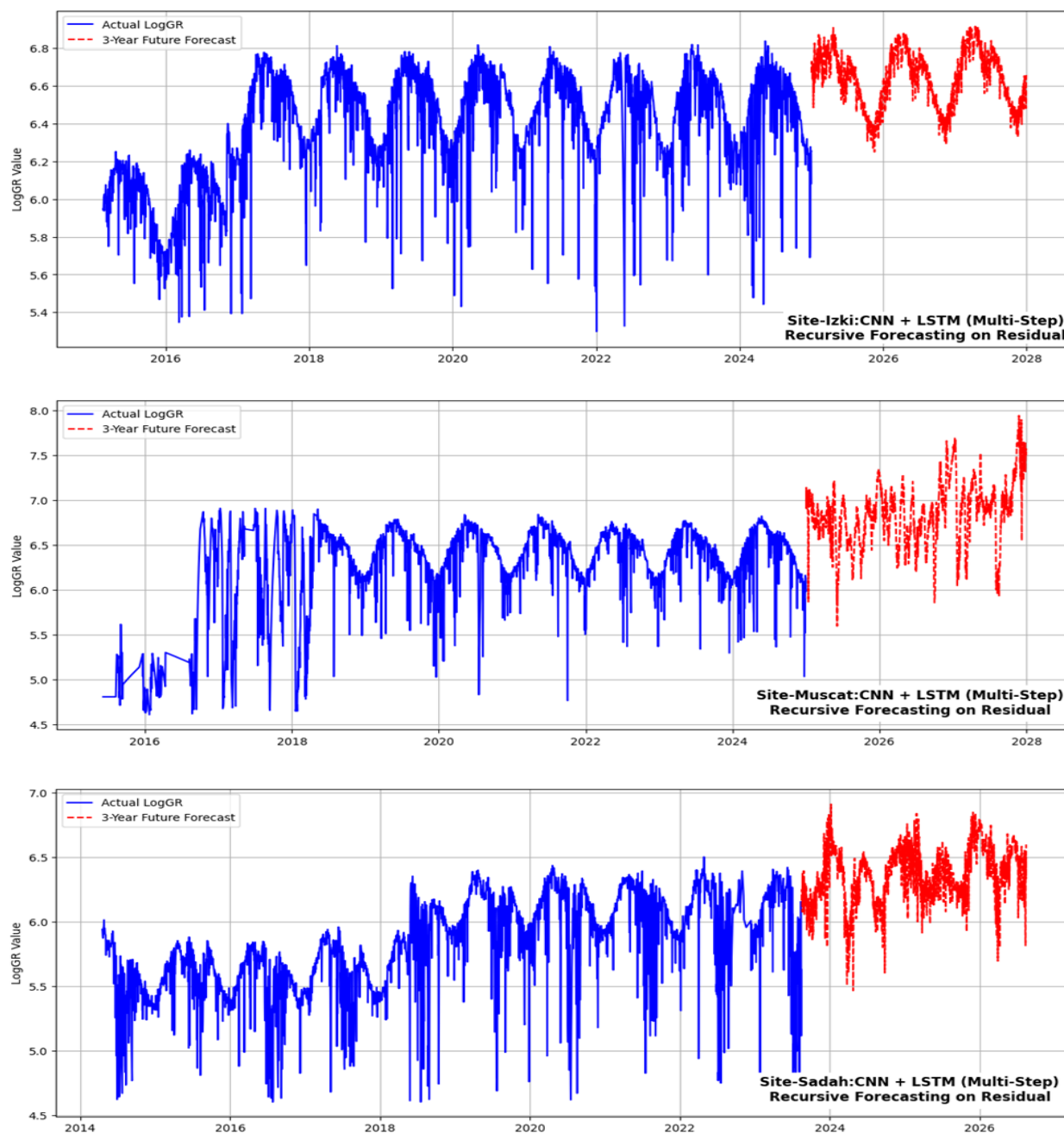


Figure 12. Time-series forecasting (three years) of global radiation (GR) using long short-term memory (LSTM) + convolutional neural network (CNN) (multi-step) (recursive forecasting on residuals) for all three sites: Izki (forecasted beyond 2025), Muscat (forecasted beyond 2025), and Sadah (forecasted beyond 2024)

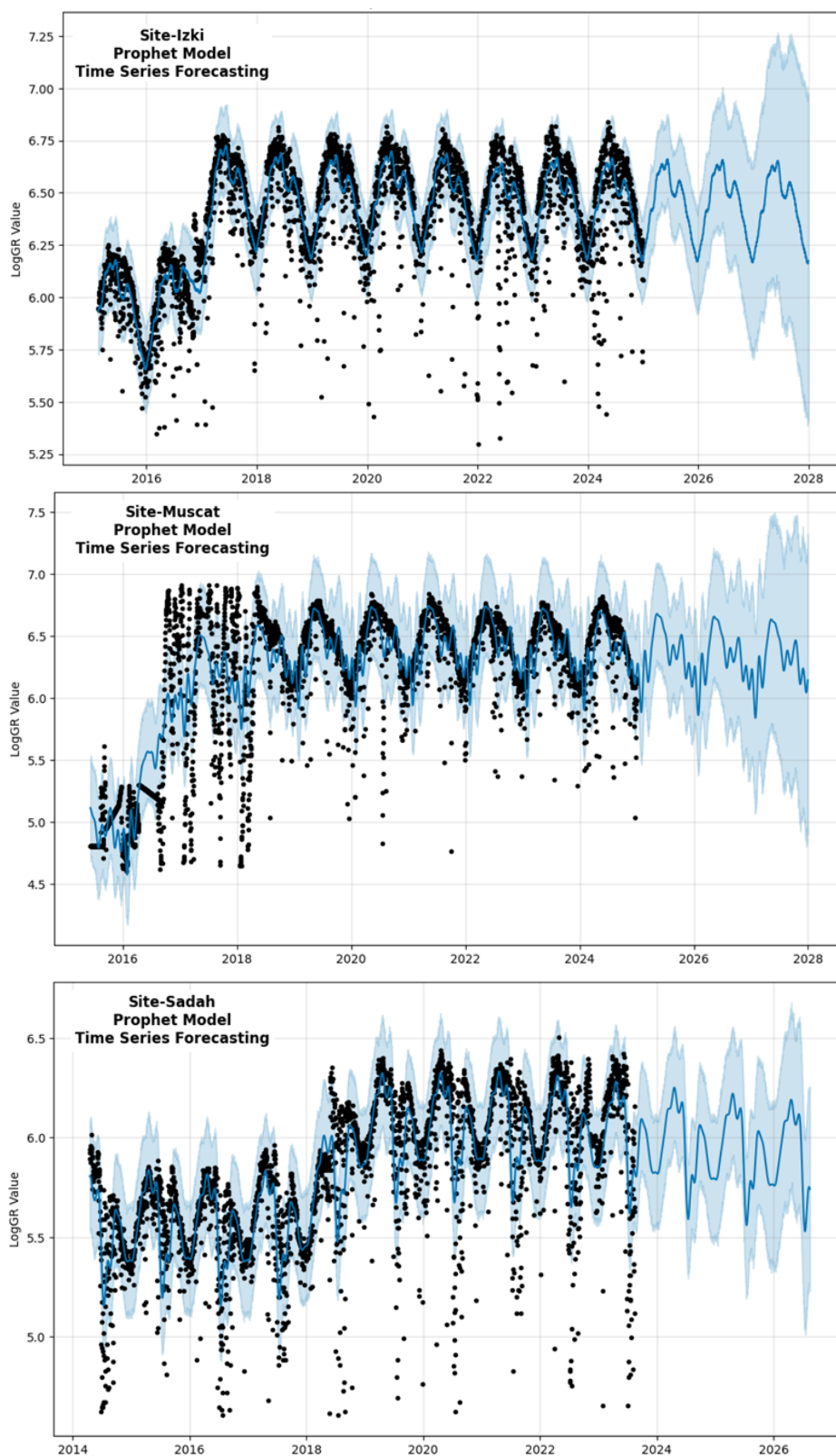


Figure 13. Time-series forecasting (three years) of global radiation (GR) using the Prophet model for all three sites: Izki (forecasted beyond 2025), Muscat (forecasted beyond 2025), and Sadah (forecasted beyond 2024)

which emphasized that local climatic dynamics must be considered in model tuning and evaluation, as data stability directly affects model generalization capacity.

4.3.3. Model interpretability vs. complexity trade-off

A critical aspect of model deployment, especially in energy management and policymaking contexts, is the trade-off between accuracy and interpretability. Classical ML models like MLR and DTR provide high interpretability due to their transparent structure. However, their performance is limited in complex, nonlinear settings—MLR achieved a validation R^2 of 0.65, while DTR reached 0.71, both significantly below ensemble or DL alternatives.

On the other hand, DL models, while offering superior performance, often function as “black boxes,” making it difficult to interpret their internal decision processes. To mitigate this, we implemented SHAP and PDP to extract and visualize feature importance. These methods revealed that latitude, cosine-transformed day of the year (DOY_{cos}), and SD were among the most impactful predictors across all model types. The use of SHAP aligns with the recommendations of Kumar *et al.* (2020), who advocated its use to enhance transparency in complex artificial intelligence systems.

5. Discussion

5.1. Influence of weather features on solar radiation

The accuracy of solar radiation forecasting is heavily influenced by the choice and significance of meteorological features. In this study, SD, vapor pressure, and temperature were found to be the most impactful predictors across all ML models. This is consistent with prior findings, where SD has been emphasized as the primary determinant of solar irradiance due to its direct relationship with the amount of sunlight reaching the surface (Motahhir *et al.*, 2020). Vapor pressure, an indicator of atmospheric moisture, plays a critical role by affecting cloud formation and the transmissivity of solar radiation. Temperature, although indirectly, influences solar panel efficiency and atmospheric clarity, making it a valuable supporting variable in forecasting models.

Traditional statistical models often fail to capture the complex interdependencies among meteorological variables, leading to suboptimal performance. In contrast, ML models excel at handling nonlinearity and variable interactions. For example, nonlinear models like random forest and LSTM networks effectively disentangle these relationships, offering significant improvements over baseline models such as MLR. These findings are further supported by feature attribution techniques that quantify each predictor's influence on model outputs.

5.2. Benefits of hybrid and ensemble approaches

The comparative analysis of model architectures revealed that hybrid and ensemble approaches consistently outperformed individual models in terms of prediction accuracy, robustness, and generalization. Specifically, ensemble learning methods, such as GB and random forests, have demonstrated superior accuracy and lower error rates by aggregating multiple learners and mitigating overfitting. The use of model averaging and boosting improved bias-variance trade-offs and enhanced the stability of predictions, a behavior observed in various energy forecasting studies (Notton *et al.*, 2018; Yap *et al.*, 2020).

Hybrid DL architectures that combine the temporal sensitivity of LSTMs with the local pattern-extraction capabilities of CNNs further improve forecasting performance. These architectures capture both sequential dependencies and spatially structured features in meteorological time series. Such synergistic designs have shown strong performance across multiple forecasting horizons, particularly in Seq2Seq configurations, confirming their adaptability to complex, multivariate solar data. Prior work has also emphasized the effectiveness of combining different neural architectures to improve deep model interpretability and predictive power (Ghimire *et al.*, 2019).

While simpler models like decision trees offer faster training and easier interpretability, they lack the generalization capacity needed for high-variance and highly nonlinear meteorological inputs. This makes them less suitable for operational deployment where accuracy is a primary concern.

5.3. Temporal patterns and forecast reliability

The design of the forecasting strategy—whether multi-step or recursive—plays a significant role in capturing the temporal dynamics of solar radiation. Multi-step models demonstrated greater long-range forecasting stability and greater resilience to error propagation. These models effectively tracked seasonal and diurnal cycles, leveraging memory structures and feature lags to improve temporal resolution. This aligns with research showing that DL-based autoregressive models tend to outperform traditional recursive schemes in medium to long-term forecasts (Yap *et al.*, 2020).

Recursive models, although generally more sensitive to accumulated forecast errors, performed competitively when augmented with exogenous inputs or residual correction mechanisms. In particular, architectures employing LSTM + CNN hybrids in recursive mode with residual learning exhibited strong resilience to volatility,

especially under variable atmospheric conditions. These enhancements enabled more accurate forecasts even during anomalous periods such as dust storms or abrupt cloud cover—a challenge commonly noted in desert and coastal climates.

Another key insight is that larger, deeper architectures with more trainable parameters offer better expressive power but require careful regularization, extensive training data, and parameter tuning. Balancing model complexity with input quality and forecast horizon length is, therefore, critical for reliable deployment.

5.4. Practical considerations for deployment

While DL and ensemble models offer high accuracy, their deployment in real-world scenarios involves several practical trade-offs. Baseline models like Prophet, although less accurate, provide advantages in terms of fast training, low computational cost, and strong interpretability. They are particularly suitable for edge deployments or integration into early warning systems, where real-time responses are prioritized over precision (Koprinska *et al.*, 2018).

In contrast, deep hybrid models require significant computational resources during both training and inference. They also require high-quality, continuous meteorological data and careful management of missing values and sensor errors. Regular retraining, performance monitoring, and interpretability tools, such as SHAP values, are essential to maintaining model transparency and building stakeholder trust.

Furthermore, integrating forecasts into energy systems—such as smart grid optimization or PV scheduling—necessitates reliable quantification of prediction uncertainty and performance under extreme weather conditions. As hybrid models continue to evolve, including attention-based transformers and physics-informed learning, the balance between interpretability, scalability, and accuracy will remain a central consideration in operational solar forecasting.

6. Conclusion

This study presented a comprehensive framework for long-term solar radiation forecasting across diverse Omani locations, integrating ML and DL techniques, advanced feature analysis, hybrid architectures, and ensemble strategies. By incorporating high-resolution meteorological variables and leveraging SHAP explainability, the research highlighted the critical influence of features such as temperature, solar radiation, and SD in driving PV output predictions. The deployment of multiple regression

models—including MLR, DTR, RFR, GBR, XGBR, and ensemble methods—demonstrated that ER yielded the highest predictive accuracy ($R^2 = 0.96$), underscoring the advantage of model aggregation for complex environmental datasets.

In parallel, DL architectures such as LSTMs, CNNs, and their hybrid forms (Seq2Seq and recursive) effectively captured temporal dependencies and spatial correlations, particularly in multi-step settings. The LSTM + CNN recursive models with exogenous features showed superior generalization and robustness, offering a promising solution for real-world solar PV forecasting. Seasonal analysis further confirmed model sensitivity to temporal variation, with improved performance in high-irradiance months.

The study affirms that hybrid and ensemble models outperform conventional methods in both accuracy and interpretability, supporting their adoption in energy management systems. Future work may focus on incorporating satellite-derived features, real-time sensor data, and adaptive learning for continuous model improvement.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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Availability of data

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Further disclosure

During the preparation of this study, the author(s) used GenAI tools for the purposes of text editing. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

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